THREE ESSAYS ON THE IMPACTS OF TRADE LIBERALIZATION

A Dissertation
Presented to
The Academic Faculty

By

Tongyang Yang

In Partial Fulfillment
of the Requirements for the Degree
Doctor of Philosophy in the
School of Economics

Georgia Institute of Technology

August 2021

THREE ESSAYS ON THE IMPACTS OF TRADE LIBERALIZATION

Thesis committee:

Dr. Tibor Besedeš, Co-advisor
The School of Economics
Georgia Institute of Technology

Dr. Julie Hotchkiss
Research Economist and Senior Adviser
Federal Reserve Bank of Atlanta

Dr. Seung Hoon Lee, Co-advisor
The School of Economics
Georgia Institute of Technology

Dr. Usha Nair-Reichert
The School of Economics
Georgia Institute of Technology

Dr. Melissa Banzhaf
Economist
U.S. Census Bureau

Date approved: June 16, 2021

For my husband and my parents. I could not be where I am today without their never-ending support, love, and understanding.

ACKNOWLEDGMENTS

My six years' journey at Georgia Institute of Technology has been memorable and would not be complete without the generous support from many people. First, I would like to express my sincere gratitude to my advisors Dr. Tibor Besedeš and Dr. Seung Hoon Lee. Dr. Tibor Besedeš has always been patient and kind and has provided me with invaluable support that helped me succeed in research and beyond. Dr. Seung Hoon Lee has continuously provided encouragement to my Ph.D. life since the first day I was on campus and supported me through many challenging times. They have made a tremendous impact on me being a teacher and a researcher of integrity, and I know I will be carrying this legacy and impact my students in the future.

I would also like to thank my RDC supervisors Dr. Julie Hotchkiss and Dr. Melissa Banzhaf. I would not have been working for Atlanta RDC for three years without them. They are amazing mentors who created a collaborative, encouraging, and delightful working environment that allowed me to progress academically and personally. I am grateful to have Dr. Usha Nair-Reichert, Dr. Karen Yan, Dr. Matthew Oliver, Dr. Aselia Urmanbetova, and Dr. Danny R. Hughes's support on my job interviews and presentations. Also, I like to thank my Ph.D. cohort, especially Marcie and Archana, who greatly supported me during the challenging job market year.

I acknowledge Georgia Tech's Grad Groups, Center for Teaching and Learning, and Leadership Education and Development in cultivating me into a person with wonderful extra-curricular experiences and being the best version of myself.

Last but not least, My family. My husband Boyang and my mom Rongmin have always been the people who console me in times of sorrow and uplift me in times of joy. Words cannot express how much I owe them. Thank you for always being by my side, accompanying me throughout my life, and always being the ones in whom I find happiness.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

SUMMARY

This dissertation examines how a negative income shock induced by globalization affected US local economies through various channels, including labor market outcomes, crime rates, and poverty.

The first chapter provides empirical results that trade liberalization with China reduced gender gaps in local U.S. labor markets. In MSAs with higher exposure to trade liberalization, the simple wage gender gap decreased, while the residual wage gap increased, indicating important selection effects in labor force participation decisions. The reduction in the gender labor force participation gap was driven by higher entry of women, in particular more educated women, and exit of the less educated men. This results in intrahousehold adjustments in work dynamics, with women entering the labor force to offset the lost income of male partners who left the labor force. We show that trade liberalization increased female workers' unemployment rate and reliance on part-time jobs.

The second chapter provides empirical evidence that regions with higher minimum wage experienced reductions in crime after trade liberalization with China. Estimation shows that a negative income shock resulting from trade liberalization with China caused a rise in property crimes, while a higher minimum wage had a buffering effect on crimes. Notably, the most significant impact was on young adults aged 20-29. A higher minimum wage may bring younger workers to the labor market, thereby reducing potential property crime rates. This chapter suggests that a higher minimum wage could function as a form of insurance as it reduces crime in the presence of a negative income shock.

The third chapter examines US-China trade liberalization's effect on socioeconomic indicators. We employ the Multidimensional Deprivation Index (MDI) and estimate the difference-in-difference model. Results show that young adults aged 17-24 experienced significant multidimensional deprivation mainly due to highschool education deprivation. There may also exist inter-generational spillover effects within the household - parents'

labor market displacement due to trade liberalization may impact their children's wellbeing. Additionally, minimum wage and social welfare expenditures do not help alleviate the multidimensionally deprived population. This finding confirms that there was not much overlap between the income poor and those who were multidimensionally deprived.

CHAPTER 1

TRADE LIBERALIZATION AND GENDER GAPS IN LOCAL LABOR MARKET OUTCOMES: DIMENSIONS OF ADJUSTMENT IN THE UNITED STATES

The following chapter is a reprint of a published chapter:

Besedeš, T., S. H. Lee, and Yang (2021). Trade liberalization and gender gaps in local labor market outcomes: Dimensions of adjustment in the United States. *Journal of Economic Behavior & Organization*, 183, 574-588.

1.1 Introduction

This chapter considers the impact of trade liberalization on gender inequality in local labor markets. We examine the effect of the US granting China Permanent Normal Trade Relations (PNTR) on the gender wage and labor-force-participation gaps in the US. We show that the liberalization of US trade relationship with China reduced both gaps in local labor markets. These changes occurred because women entered the labor force, while men left the labor force as the exposure to China receiving PNTR status affected manufacturing industries more which tend to employ relatively more men. Our results indicate that women entered the labor force in part to offset the reduction in family income that occurred as their male partners lost jobs and left the labor market.

We use the Pierce and Schott (2016, 2020) approach to measure a local labor market's exposure to trade liberalization. Pierce and Schott (2016) show that granting permanent normal trade relations to China in 2001 caused a sharp decline in US manufacturing employment in the 2000s. They argue that Chinese exporters faced significant risks of increased tariffs before 2001 since China's Normal Trade Relations (NTR) status, guaranteeing low tariffs when exporting to the US, required annual renewals by the Congress. Pierce and Schott (2016) define PNTR exposure as the difference between the high non-

NTR tariffs and the much lower NTR tariffs, which averages to 33 percentage points in 1999. The conferral of PNTR status to China eliminated tariff uncertainty and brought the decline in US employment by encouraging Chinese exporters to scale up and US firms to do more offshoring/outsourcing. In a follow-up paper, Pierce and Schott (2020) calculate the exposure level to PNTR for each US county and show that a county's higher exposure to PNTR is associated with increases in mortality from stress-related causes (e.g., suicides), specifically among white males. Our investigation focuses on Metropolitan Statistical Areas (MSAs), which are defined along the lines of local labor markets with sufficiently high population density at their core. We find that a Metropolitan Statistical Area (MSA) with higher PNTR exposure experienced a decrease in gender gaps in wage and labor force participation rates (LFPR) after trade liberalization with China. We examine both the simple and residual wage gender gaps. The simple gender wage gap decreased after China received PNTR status, and this finding is unaffected once we control for selection. However, we also show that there were some selection effects in the wake of China receiving PNTR status. The residual wage gap actually increased, showing that, once controlling for observable worker characteristics such as education levels, men earned higher wages than women. The two results are reconcilable as long as this shock made the male labor market relatively more competitive by generating different selections for the two genders as less educated men left the labor force or more educated women entered the labor force in greater numbers. We find evidence of both of these effects. MSAs with higher PNTR exposure experienced larger increases in female relative labor force participation rates, and this increase was largely driven by the entry of more educated women into the labor force, where the more educated women are those with at least some college-level education. We also find that labor force participation rates decreased for men, somewhat more strongly for the less educated men.

The greater participation in the labor force by women was a response to how China receiving PNTR status affected households. We show that MSAs with higher exposure did not experience change in the share of households with both spouses working, but there was a significant decrease in the share of households with only the husband (or male partner) working and an increase in households with just the wife (or female partner) working. In addition, the share of family income accounted for by the female partner has increased in MSAs with greater exposure to China's PNTR status. The greater labor force participation rates of women also resulted in higher unemployment for women, while males exiting the labor force did not prevent higher unemployment among them which was also accompanied by a reduction in employment among men. Furthermore, in MSAs with higher PNTR exposure, female workers spent more time in part-time employment. The increase in part-time employment is a consequence of individuals not being able to find full-time employment, rather than wanting to work only part-time.

Other studies have found significant effects of trade liberalization on labor market outcomes and gender inequality using different methodologies. Autor, Dorn, and Hanson (2013) explain the decline in US manufacturing employment with Chinese import penetration. Their estimation strategy, to instrument the growth of Chinese exports to the US by the growth of Chinese exports to other high-income countries, was adopted by a number of follow-up papers. Following their identification strategy, Brussevich (2018) shows that US commuting zones with higher import penetration show greater reduction in the gender wage gap and that wage and welfare gains from trade are higher for female workers since the import competition shock in manufacturing sector disproportionally affected the labor market outcomes of the two gender groups. Greenland, Lopresti, and McHenry (2019) found that commuting zones with greater exposure to China gaining PNTR status experienced reduced population growth, particularly for men. Benguria and Ederington (2017) show that increased competition from China lowered the gender wage gap in Brazil, which is driven by the underperformance of male workers. Other trade liberalization episodes have also been found to have reduced gender wage gaps. Aguayo-Tellez et al. (2014) show that tariff reductions, accompanied by the North American Free Trade Agreement

(NAFTA), increased the demand for female labor and raised their relative wage in Mexico. Juhn, Ujhelyi, and Villegas-Sanchez (2014) find that NAFTA raised the relative wage and employment of female workers, especially in blue-collar tasks in Mexico. They explain that higher competition encouraged firms to modernize their technology, thus reducing their dependence on physical ability. Ederington, Minier, and Troske (2009) report that tariff reductions in Chile, as a result of Chile's entry into GATT/WTO, raised the number of female workers (relative to male ones) in blue-collar jobs. Similar to Brussevich (2018), Black and Brainerd (2004) show that import penetration is associated with greater reductions in the gender wage gap in the US.

Some researchers have shown that gender inequality can increase with trade liberalization. Sauré and Zoabi (2014) report that the formation of NAFTA widened the gender gaps in the US labor market. Since female intensive sectors tend to be capital intensive, trade liberalization between capital-rich and capital-poor countries may raise the gender gap in the capital-rich country (i.e., the US) by reallocating male workers into capital intensive sectors. Bøler, Javorcik, and Ulltveit-Moe (2018) report higher wage gaps for exporting firms compared to non-exporters in Norway. They claim that exporters may require a greater commitment from employees. Hence, female workers, who tend to have less flexible schedules, receive lower relative wages.

Gender inequality and trade liberalization have been an important issue investigated in the literature. This chapter shares similar insights and findings with previous papers in part. Our chapter shares similar insights with Sauré and Zoabi (2014), Benguria and Ederington (2017), and Brussevich (2018), in that trade liberalization affects gender inequality in the labor market through reallocation of male labor from the male-intensive sector. However, our chapter makes an important contribution since we explain how the various channels are connected by examining both the simple and residual wage gaps. We explore gender gaps both in wage and labor force participation whereas most existing papers focus on wage inequality. We also propose possible mechanisms through multiple channels including education level and marital status, the former of which help explain the selection effects induced in local labor markets by China receiving PNTR status. We also provide additional insights into the effects of trade liberalization in developed economies and show that with respect to the effect on gender gaps, trade liberalization has similar effects in developed and developing countries. The latter conclusion is based on the similarity between our results for the US and Benguria and Ederington (2017)'s results for Brazil. We show that trade liberalization has affected the overall quality of female jobs by increasing part-time work at the expense of full-time employment. Our chapter is related to Charles, Hurst, and Schwartz (2019), who show that the manufacturing decline in a local labor market in the 2000s had negative effects on local employment rates, hours worked, and wages. They find larger negative effects employment of men and for the less educated workers. Their findings are consistent with ours in that the negative effects from China gaining permanent normal trade relations are larger for male workers and the less educated group.

Lastly, our chapter is related to a set of papers which examine intrahousehold or intrafamily adjustments to trade liberalization and offers new and interesting findings. Autor, Dorn, and Hanson (2015) find that local labor markets more exposed to Chinese imports experience a decrease in employment, especially in manufacturing and among non-college workers. Dorn, Hanson, et al. (2019) examine the effects of increased competition from China on young adults in the US finding an increase in male idleness and premature mortality as well as reductions in marriage and fertility, and an increase in the fraction of single mothers who are heads of households, as well as an increase in the number of children living in poverty. Keller and Utar (2018) show that increased competition from Chinese imports in Denmark resulted in a shift towards the family, with an increase in parental leave, fertility, marriage, and a reduction in divorce rates.[1] We find opposite results the married women in the US entering the labor force and to some extent shifting away from the family. Hakobyan and McLaren (2017) show that the impact of trade liberalization on female

[1] Using our data, we examined the effect on divorce rates and childbirth rate, but find no significant effects. These results are available on request.

wages depends on marital status. They observe that married low-skilled women experienced larger reductions in wage growth with respect to NAFTA tariff reductions than other demographic groups since high-skilled women drop out of the labor market. Our chapter indicates that the shock due to China gaining PNTR status was different than NAFTA as the former induced more educated and higher-skilled women to enter the labor force. Thus, our results stand in contrast to both Hakobyan and McLaren (2017) and Keller and Utar (2018) as we examine the reduction in gender gaps by exploring monetary incentives of married females who had to compensate for lost family income from the negative income shock. The shock created by China receiving PNTR status is well recognized to have brought important changes to the US society. Our chapter provides a good understanding of this important event from the perspective of female workers.

1.2 Data

1.2.1 Labor Market Outcomes

We measure labor market outcomes using Current Population Survey's (CPS) Annual Social and Economic Supplement (ASEC), a nationally representative household data with detailed information of each household member's earnings, work hours, gender, and race, among other indicators. We restrict our sample to individuals who are older than 25 and younger than 64 and are either in or out of the labor force for reasons not related to being on active military duty or having a disability.[2] Our sample in 2000 includes 49,700 individuals who resided in 272 MSAs with trade liberalization exposure data. Table 1.1 shows the demographic characteristics of our sample in three years, 1990, 2007, and 2013. Women account for 52 percent of our sample in every year. Male workers' dependency on manufacturing in the labor market is almost twice as large as female workers' before and after the

[2]For variables that require only those who are working, we further restrict the sample to include workers with a stronger attachment to the labor market - worked for more than 20 weeks in the previous year, and more than 35 hours per week in the previous year (both inclusive), following Maasoumi and Wang (2019).

conferral of permanent trade relations to China.[3] Artuç, Chaudhuri, and McLaren (2010) show that high switching costs across sectors slow down the readjustment of an economy in response to a trade shock. Hence, the heavier dependency on manufacturing sector on the part of male workers may have aggravated the impact on the male labor market. Table 1.1 displays the familiar patterns by now: the share of manufacturing in the US economy has steadily declined, from 15.2% of individuals in 1990 to 9.2% in 2013. This decrease has occurred at the expense of services which have grown from 53.7% of individuals to 61.3%.

To understand the differential impact by educational attainment, we divide all individuals in our sample into two levels of education, those without any college education and those with at least some, even if they do not have a college degree.[4] About 43 percent of our sample had some college education in 1990 while the education levels of two gender groups are not significantly different from each other. By the end of our sample the share of individuals without college education has declined to 37%, with women comprising a larger share of individuals with some education by 2013.

Table 1.1: CPS sample composition across time

	1990			2007			2013		
	Female	Male	Total	Female	Male	Total	Female	Male	Total
By sector									
Manufacturing	5.3%	9.9%	15.2%	3.4%	7.0%	10.4%	2.8%	6.4%	9.2%
Services	29.7%	24.0%	53.7%	34.0%	26.4%	60.4%	34.3%	27.1%	61.3%
Other	17.2%	14.0%	31.2%	14.8%	14.4%	29.2%	15.2%	14.2%	29.4%
By education									
No college experience	31.0%	26.1%	57.1%	20.1%	20.5%	40.6%	17.9%	19.1%	37.0%
Has college experience	21.2%	21.7%	42.9%	32.1%	27.3%	59.4%	34.4%	28.7%	63.0%
Total	52.2%	47.9%	100.0%	52.2%	47.8%	100.0%	52.3%	47.8%	100.0%

Our variables of interest, summarized in Table 1.2, include the average hourly wage,

[3] We can observe a worker's industry from industry codes provided by CPS. We classify a worker's industry as services if she or he is in transportation, communications, public utilities, wholesale trade, retail trade, finance, insurance, real estate, business and repair services, personal services, entertainment and recreation services, or professional and related services. If the worker does not belong to either manufacturing or services, we assign her or him "other" sector.

[4] Our definition for education group follows Maasoumi and Wang (2019), who split their samples into four classes: below high school education, high school degree, some college experience, and above college degree. We aggregate their classifications into two groups, at least some college education and less than college education, due to the insufficient number of individuals in an MSA if we apply the same classification as Maasoumi and Wang (2019).

w_{it}, the number of total hours worked, h_{it}, and labor force participation status, l_{it}, of an individual i in year t. The number of total work hours, h_{it}, is calculated by multiplying "Usual work hours worked per week last year" and "Weeks worked last year," and reflects the total number of hours the individual spent working in the previous year. The hourly wage, w_{it}, is calculated as "Wage and salary income" divided by the number of total hours worked, h_{it}. We directly observe an individual's labor participation status, l_{it}, from the variable "Labor force status" and consider individual i is in the labor force if she or he worked, was looking for a job, or was temporarily absent/laid-off during the reference period.

Table 1.2: Summary statistics of CPS variables (means)

	1990			2007			2013		
	Female	Male	Total	Female	Male	Total	Female	Male	Total
Wage	9.52	12.66	10.79	17.96	22.62	21.41	20.47	25.65	23.16
	(1.69)	(2.29)	(2.61)	3.62	5.50	13.35	4.35	5.80	6.55
Work Hours	1,705.6	2,113.6	1,920.8	1,818.6	2,132.9	1,994.0	1,794.5	2,081.1	1,937.9
	(139.8)	(123.4)	(113.2)	127.0	107.8	91.3	140.1	146.3	99.7
Labor Force Participation Rate	70.18%	89.92%	79.72%	77.67%	91.64%	84.41%	77.37%	89.76%	83.33%
	(0.10)	(0.05)	(0.07)	0.08	0.05	0.52	0.09	0.06	0.06

Note. Standard deviation in parentheses.

In 1990, the average hourly wage for the whole population was \$10.79, with the average female hourly wage of \$9.52, equivalent to 75 percent of the average male hourly wage. In 2007, the female worker's average wage increased to about 79 percent of the male worker's and to 80 percent in 2013.[5] We observe similar patterns for other variables. In 1990 female workers' average work hours were equivalent to 81 percent of male average work hours. It increased to 85 percent by 2007 and 86 percent in 2013. In 1990 the labor force participation rate (LFPR) of female workers was about 20 percentage points lower than that of their male counterparts. In 2007, the gap decreased to about 15 percentage points and to 13 percent by 2013. Our data reveal the well-known patterns: while male workers tend to outperform female workers, gender gaps have been on the decline.

We are interested in regional differences in changes in gender gaps. For this purpose,

[5]The median female wage increased from 75 percent of the male wage in 1990 to 80 percent in 2010.

we calculate weighted averages of the above variables at MSA levels.[6]

$$w_{mt}^S = \frac{1}{\hat{N}_{mt}^S} \sum_{i \in S \cap m} w_{it}, \quad l_{mt}^S = \frac{1}{N_{mt}^S} \sum_{i \in S \cap m} l_{it}, \quad h_{mt}^S = \frac{1}{\hat{N}_{mt}^S} \sum_{i \in S \cap m} h_{it}$$

where m indicates an MSA, S refers to demographic groups, N_{mt}^S is the number of individuals of group S who resided in MSA m in year t, and $\hat{N}_{mt}^S$ is the number of individuals with a positive w_{it}. For example, if we let F be the set of females, then l_{mt}^F refers to labor force participation rate of females in MSA m and year t. Unlike Pierce and Schott (2020) who conduct their analysis using county-level data, we perform our analysis using MSA-level data. As we are interested in labor market outcomes, we conducted our analysis at the MSA level since they are largely defined by boundaries of local labor markets.[7]

1.2.2 NTR Gap

Our measure of exposure of an MSA to trade liberalization follows Pierce and Schott (2020). Their measure is based on the difference between two tariff rates in the US tariff schedule that could be assessed on imports from China. Imports from a country which does not have normal trade relations with the US are assessed tariff rates established by the Smoot-Hawley Tariff Act of 1930. These rates are significantly higher than the normal trade relation tariffs rates, which are assessed on imports from countries that are members of the World Trade Organization (WTO). China was first granted temporary NTR status in 1980 with a provision that its status be reaffirmed on an annual basis. The uncertainty associated with renewal was a function of various crises in US-China relations during the 1990s. China was finally granted permanent normal trade relations with the US in October 2000 as a prelude to its entry into the WTO in December 2001.

We follow Pierce and Schott (2020)'s methodology to measure a local labor market's

[6]When we calculate MSA-level variables, we use ASEC asecwt weights as CPS suggests.

[7]Using commuting zones (CZs), which cover the entire country, may be a better option, but not a feasible one since CPS's county identifier needed to calculate CZ-level labor market outcomes is only available since 1996.

exposure to trade liberalization. We start with their industry-level measure, $NTRGap_j$, defined as the difference between non-NTR rates and NTR rates in a six-digit NAICS sector j:

$$NTRGap_j = non - NTRtariff_j - NTRtariff_j$$

$NTRGap_j$ refers to the potential tariff increase on Chinese imports and captures the uncertainty faced by Chinese exporters in industry j.

Table 1.3: MSAs with the highest and lowest NTR Gaps

Rank	Metropolitan Statistical Area (MSA)	NTR Gap
1	Hickory-Morganton, NC	0.235
2	Burlington, NC	0.212
3	Danville, VA	0.198
4	Elkhart-Goshen, IN	0.170
5	Rocky Mount, NC	0.165
316	Bismarck, ND	0.038
317	Billings, MT	0.038
318	Great Falls, MT	0.036
319	Las Vegas, NV	0.034
320	Farmington, NM	0.031

Using $NTRGap_j$, Pierce and Schott (2020) calculate a county's exposure to PNTR. We follow the same steps and calculate the exposure to PNTR for metropolitan areas:

$$NTRGap_m = \sum_j \frac{L_{jm}^{1990}}{L_m^{1990}} - NTRGap_j$$

where L_{jm}^{1990} refers to the number of employees in sector j in MSA m in the year 1990 and L_m^{1990} refers to the total number of workers in MSA m. The information about employment weights, L_{jm}^{1990} and L_m^{1990}, are from the County Business Patterns (CBP), an annual dataset with information on employment and payroll by sector and county. Higher $NTRGap_m$ indicates a higher exposure of MSA m to trade liberalization with China. $NTRGap_m$ has a mean 0.145 and standard deviation 0.05. Table 1.3 lists the MSAs with the highest and lowest $NTRGap_m$, while Figure 1.1 illustrates the geographical distribution of $NTRGap_m$. MSAs in the mid-Atlantic and Midwest regions are more exposed to trade liberalization.

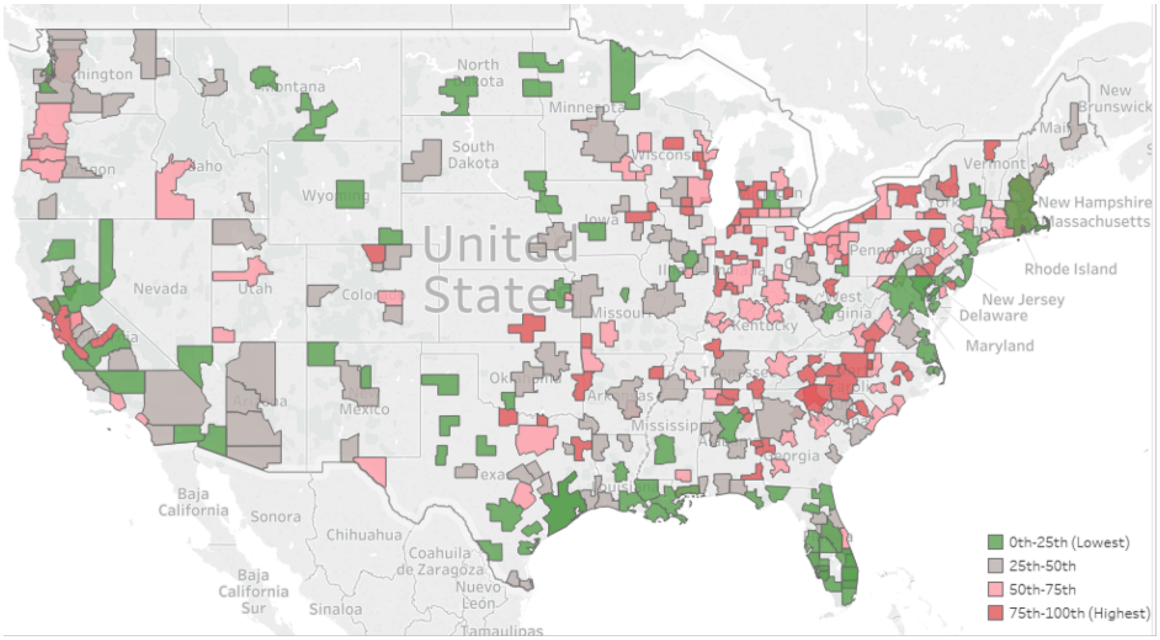


Figure 1.1: Geographic distribution of $NTRGap_m$

1.3 Estimation

1.3.1 DD identification Strategy

Our estimation strategy follows Pierce and Schott (2020). Our baseline difference-in-differences (DD) specification examines whether MSAs more exposed to PNTR (first difference) experience differential changes in gender gaps in wage and labor force participation rates after the change in US trade policy versus before (second difference),

$$\begin{aligned} LHS_{mt} &= \theta \cdot PostPNTR_t \times NTRGap_m + \beta \boldsymbol{X}_{mt} \\ &\quad + \gamma \cdot PostPNTR_t \times \boldsymbol{Z}_m + \delta_m + \delta_m + \varepsilon_{m,t}. \end{aligned} \tag{1.1}$$

The dependent variable LHS_{mt}, a local labor market outcome such as the gender wage or labor-force-participation-rate gap, is defined in year t for an MSA m. The first term on the right-hand side is the DD term of interest, an interaction of a post-PNTR (i.e., $t > 2000$) indicator with the (time-invariant) MSA-level NTR Gap. $\boldsymbol{X}_{mt}$ represents the (time-varying) overall US import tariff rates associated with the industries active in the MSA as well as exposure to the elimination of the Multi-Fibre Agreement quotas which took place in 2002 and 2005. $\boldsymbol{Z}_m$ represents the initial-period MSA attributes, 1990 median household income, 1990 share of population without any college education, 1990 share of population that are veterans, and its exposure to changes in Chinese imports tariffs. δ_m and δ_t refer to MSA and year fixed effects. We cluster standard errors at MSA levels. The sample period is 1990 to 2013 as in Pierce and Schott (2020).

1.3.2 Estimates of the Gender Wage Gap

We begin our analysis by focusing on the gender wage gap. We find that MSAs with higher NTR Gap and higher exposure to PNTR have lower labor market gender gaps after the conferral of PNTR in 2001. We use Equation 3.1 with female-male wage ratio, w^F_{mt}/w^M_{mt}, the gender wage gap, as the dependent variable and estimate the DD point estimate of interest, θ. The first and second columns of Table 1.4 report the results for the female-male wage ratio. The first column reports coefficient estimates for a specification containing just the DD term of interest and fixed effects. The second column adds controls for policy changes $\boldsymbol{X}_{mt}$ and demographic variables $\boldsymbol{Z}_m$.[8] The DD point estimates of interest are positive ($\theta > 0$) and statistically significant at conventional levels across all columns. Our empirical results suggest that higher import competition from China is associated with a lower gender wage gap in US labor market outcomes, as in Brussevich (2018).

Our main question is to understand which changes in local labor market outcomes drive changes in gender gaps. As a first step, we examine changes in wages of women and men. We estimate Equation 3.1 by using the log value of the wage, $\log(w^S_{mt})$, for each gender $S \in F, M$ as dependent variables and collecting results in columns 3 and 4 of Table 1.4.

[8] Given the number of tables and results in the chapter, in certain tables we only report the estimates from the specification with additional controls out of concerns for space. All other results are available on request.

Our results suggest that female wages increased, while that of men may have decreased, though the latter coefficient is not estimated with much statistical precision. The reduction in the gender wage gap is likely a consequence of both an increase in female wages and a decrease in male wages, but our data preclude us from identifying those changes in wages precisely. To put it differently, the increase in female wages and the decrease in male wages on their own may be statistically insignificant, but taken together their changes in opposite directions combine to result in a statistically meaningful reduction in the gender wage gap.

Table 1.4: Gender wage gap and wages

	All data (Benchmark sample)				Machado sample	
	Female Wage/Male Wage		Female Wage	Male Wage	Female Wage/Male Wage	
Post * NTR Gap	0.418*	0.678**	0.597*	-0.206	-0.705	1.447*
	(0.241)	(0.338)	(0.343)	(0.413)	(0.948)	(0.828)
NTR rate		1.632*	1.166	-0.567		7.261*
		(0.854)	(0.749)	(0.780)		(3.875)
MFA rate		1,567	-628.0	-2,391		9929
		(3,202)	(3,180)	(4,623)		(13200)
Post * Chinese tariff		-0.0371	0.834	0.942		2.965
		(0.605)	(0.720)	(0.841)		(3.202)
Post * No College		-0.000324	-0.167***	-0.169***		0.211
		(0.0638)	(0.0595)	(0.0612)		(0.274)
Post * Veteran		0.235*	0.235*	-0.00420		0.890
		(0.141)	(0.120)	(0.107)		(0.794)
Post * Median HHI		0.0291	0.0639***	0.0318		0.198
		(0.0221)	(0.0209)	(0.0252)		(0.121)
Observations	5,429	5,356	5,356	5,357	5,372	5,302
R^2	0.124	0.129	0.781	0.741	0.067	0.071

Note. Standard errors clustered on MSAs in parentheses, MSA and year fixed effects.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Before examining selection and the residual wage gap, we examine whether there are sectoral differences in the behavior of the wage gap and wages themselves. To that end, we take advantage of the information on the sector in which employed individuals were working and classify them as either manufacturing, services, or other in Table 1.1. We then estimate for each of the three sectors the wage gap as well as female and male wages and collect results in Table 1.5.[9] The reduction in the wage gap in the wake of China attaining permanent normal trade relations seems to be largely driven by the services sector

[9]To conserve space for the remainder of the chapter we present results only from the specification which includes additional explanatory variables. Complete results are available on request from authors.

which experienced a large and significant reduction in the gender gap, while the manufacturing sector experienced a widening gender wage gap. Unfortunately, similar to our wage regressions pooling across all sectors, our results for changes in wages in each sector are not precise enough, preventing us from drawing strong conclusions. Changes for male and female workers alone are not precisely estimated, but taken together they indicate a reduction in the gender gap in the services sector and an increase in the gender gap in the manufacturing sectors. Our estimates suggest that while both male and female wages decline in manufacturing, female wages decline more. That wages in manufacturing declined is not a surprise given the Pierce and Schott (2016) finding of a reduction in manufacturing employment.

In order to consider the role of selection and entry/exit dynamics in our wage outcomes, we estimate Equation 3.1 with samples restricted as Machado (2017) who proposed an estimator for the wage gap that allows for arbitrary and unobserved heterogeneity in selection. Using the National Longitudinal Survey of Youth 1979, she found that the "always employed" female subpopulation has similar characteristics as the male subpopulation in terms of labor market experience and cognitive tests. Following her methodology of restricting CPS samples, we restrict our sample to individuals who worked 50 weeks per year and 35 hours per week in the previous year to perform an apple-to-apple comparison and re-estimate coefficients regarding the gender wage gaps in Table 1.4, collecting results in columns 5 and 6 of Table 1.4. The estimated DD coefficient for the sparse specification is no longer significant, while the estimated coefficient for the specification with additional controls is marginally statistically significant and larger in magnitude, suggesting that even after controlling for sample selection issues, the gender wage gap has decreased in the wake of China receiving permanent normal trade relations status. The reduction in the precision of our estimates could be due to the selection effect, in that some of the reduction is due to changes in characteristics of individuals in the labor market, not by the changes in performance of "always employed" workers. We will return to this point later.

Table 1.5: Sectoral differences in the wage gender gap and wages

				Wage					
				Manufacturing		Services		Other	
	Manufacturing	Services	Other	Female	Male	Female	Male	Female	Male
Post * NTR Gap	-1.670**	0.891**	-0.847	-1.111	-0.0863	0.541	-0.358	1.107	0.761
	(0.836)	(0.444)	(1.020)	(0.814)	(0.646)	(0.401)	(0.460)	(0.875)	(0.517)
NTR rate	-3.198*	3.028**	0.803	-2.657	-1.483	1.009	-1.749	2.042	1.433
	(1.785)	(1.196)	(2.025)	(1.769)	(1.308)	(0.818)	(1.085)	(1.733)	(1.202)
MFA rate	11,610	5,562	-25,908**	9,438	-4,745	-2,283	-8,433	-3,426	15,760**
	(8,335)	(4,847)	(12,471)	(8,926)	(7,078)	(3,977)	(6,363)	(8,353)	(6,311)
Post * Chinese tariff	-0.559	-0.0815	0.919	0.611	1.018	0.679	0.899	2.083	0.979
	(1.470)	(0.868)	(2.089)	(1.302)	(1.156)	(0.794)	(1.019)	(1.441)	(1.079)
Post * No College	-0.0855	0.0231	-0.0610	-0.201	-0.189*	-0.190***	-0.212**	0.0599	0.0678
	(0.232)	(0.0818)	(0.171)	(0.159)	(0.108)	(0.0649)	(0.0829)	(0.121)	(0.0962)
Post * Veteran	0.223	0.288*	-0.130	-0.181	-0.342*	0.286**	0.0825	-0.284	-0.217
	(0.403)	(0.174)	(0.374)	(0.310)	(0.199)	(0.136)	(0.146)	(0.239)	(0.197)
Post * Median HHI	-0.0150	0.0353	-0.0438	0.0834	0.0237	0.0684***	0.0262	0.00343	0.0561
	(0.0753)	(0.0319)	(0.0661)	(0.0571)	(0.0448)	(0.0244)	(0.0344)	(0.0484)	(0.0360)
Observations	4,613	5,353	4,865	4,658	5,192	5,355	5,355	4,865	5,301
R^2	0.108	0.106	0.094	0.482	0.506	0.734	0.631	0.431	0.459

Note. Standard errors clustered on MSAs in parentheses, MSA and year fixed effects.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

We next examine the residual wage gap between males and females. The simple wage gap analyzed above may mask the effect of having different occupations, education, tenure, etc, on the wage gap. Following Lemieux (2006) we define residual wage as the residual term from a regression of individual worker's wage on his or her observed characteristics. To obtain the residual wage we regress wages using individual level data on the following variables: age, sex, marriage status, veteran status, occupation, level of education, industry of employment, and MSA where the individual resides. We then use the obtained residuals to estimate a variant of Equation 3.1 at the individual level. The dependent variable is the residual wage of a worker and along with the usual control variables, we include a dummy variable identifying males in the post-PNTR period, as well as an interaction of the post-PNTR dummy, the NTR gap, and the male dummy, effectively estimating a triple difference specification.[10] Our results are collected in Table 1.6.

[10] Note that as with all out regressions we estimate MSA and year fixed effects as well as a sex fixed effect. The addition of the sex fixed effect is only so that this specification is econometrically a true difference-in-differences-in-differences specification. Since the wage regression we estimate to obtain residual wages includes sex as an explanatory variable, it usually would not be used in the residual wage regression. Not surprisingly, its inclusion does not affect our estimates in a material way. It is possible to group occupations and we examined one such approach grouping "Managerial and Professional Specialty" and "Technical, Sales, and Administrative Support" occupations. Similar to sectoral regressions, we found no significant results. Out of concern for space, these results are not reported and are available on request.

Table 1.6: Residual wage gender gap

Post * NTR Gap * Male	0.185***
	(0.064)
Post * NTR Gap	-0.098
	(0.087)
Post * Male	-0.014***
	(0.005)
NTR rate	-0.001
	(0.145)
MFA rate	-15.37
	(989.8)
Post * Chinese tariff	-0.000
	(0.006)
Post * No College	0.000
	(0.014)
Post * Veteran	-0.000
	(0.031)
Post * Median HHI	-0.001
	(0.137)
Observations	1,151,394
R^2	0.000

Note. Standard errors clustered on MSA×Sex×Year in parentheses, MSA, year, and sex fixed effects. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Our results indicate that the residual gender wage gap has increased. Taken together, our results indicate that while the relative female wage has increased, the residual female wage has decreased. The implication is that the relative female wage may have increased due to the China PNTR shock generating selection effects, which would be consistent with how controlling for selection effects affected our simple wage gap regression results. It is possible that the relative female wage has increased because more educated women entered the labor force, or similarly, that more educate men left the labor force. The residual wage regression results, which control for the level of education, indicate that the quality of the male labor force has increased, as long as we assume that wages are correlated with labor productivity. Thus, the shock created by China being granted PNTR status may have had a more negative effect on the male labor market, by increasing import competition in sectors where male participation is relatively higher such as manufacturing, inducing more women to enter the labor force to compensate for the reduction in family income due to men leaving the labor force. However, there was a selection effect in the female subpopulation with more educated women more likely to enter the labor force. To better understand these effects, we now turn our attention to labor force participation effects.

1.3.3 Estimates of the Gender Labor Force Participation Gap

We begin our investigation of the gender gap in labor force participation rates (LFPR) by estimating Equation 3.1 using the LFPR gap as the dependent variable and collecting our result in the first two columns of Table 1.7. The last two columns estimate Equation 3.1 separately for female and male labor force participation rates. Our estimates for changes in labor force participation rates are much more precise. The gender gap in labor force participation rates has declined in the more exposed MSAs. This reduction is driven by both a statistically significant decline in male and a statistically significant increase in female labor force participation rates as reported by results in Table 1.7. Such changes are potentially indicative of female workers replacing male workers in the labor force or may be a consequence of a structural change in available jobs skewed in favor of women. While the latter change is beyond the scope of our chapter, later in the chapter we examine whether this shock precipitated women replacing men in the labor force within households.

In the previous subsection we noted that the results from the residual wage regression could be explained by the negative shock of China receiving PNTR status may have induced not only greater labor force participation on the part of women, but a particular pattern in selection, namely that it was the more educated women who tended to enter the labor force. We now examine whether trade liberalization had a different effect on individuals with different levels of education. We estimate Equation 3.1 with labor force participation rates of different education groups and report the estimated coefficients in Table 1.8.[11] We separate our sample by education into less and more educated, where the less educated are those with no college education and more educated are those individuals with at least

[11] As defined earlier, individuals with less education are those with no college experience while those with more education are those with at least some college education.

Table 1.7: Gender gap and labor force participation rates

	Female LFPR/Male LFPR		Female LFPR	Male LFPR
Post * NTR Gap	0.424***	0.671***	0.395**	-0.206**
	(0.139)	(0.200)	(0.166)	(0.0973)
NTR rate		1.020***	0.751***	-0.154
		(0.364)	(0.263)	(0.212)
MFA rate		-2,552	1,498	4,206**
		(2,124)	(1,700)	(1,806)
Post * Chinese tariff		0.156	0.338	0.233
		(0.326)	(0.289)	(0.171)
Post * No College		-0.000118	0.0532	0.0345*
		(0.0361)	(0.0372)	(0.0189)
Post * Veteran		-0.0184	-0.0381	-0.0624
		(0.0747)	(0.0616)	(0.0413)
Post * Median HHI		-0.0152	0.0311*	0.0323***
		(0.0146)	(0.0159)	(0.00800)
Observations	5,400	5,400	5,401	5,400
R^2	0.308	0.310	0.433	0.273

Note. Standard errors clustered on MSAs in parentheses, MSA and year fixed effects.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

some college education. The reduction in the gender gap in labor force participation rates identified in pooled results in Table 1.7 is largely driven by the increased participation of the more educated women, while the estimate for less educated women is also positive but imprecisely estimated. Labor force participation rates of all men decreases, while only that of less educated men is precisely estimated.

One interpretation of these changes is that the negative income shock experienced by families may have induced some of the more educated women who chose to be stay-at-home parents to re-enter the labor force. This is related to Hakobyan and McLaren (2017) finding that married high-skilled females drop out from labor market with respect to worsened labor market conditions due to NAFTA tariff reductions. Our results indicate that the effects of NAFTA tariff reductions and granting of PNTR status to China have at least some different effects and highlight that high-skilled females are the demographic group whose labor supply is relatively elastic with respect to negative income shocks.

With respect to the observed sectoral results, as we discussed in Section 1.2.1. and seen

Table 1.8: Labor force participation gap and labor force participation by sex and education

	Female LFPR/Male LFPR		Female LFPR		Male LFPR	
	Less educated	More educated	Less educated	More educated	Less educated	More educated
Post * NTR Gap	0.497	0.701**	0.162	0.388**	-0.346*	-0.204
	(0.379)	(0.279)	(0.233)	(0.193)	(0.182)	(0.130)
NTR rate	0.045	1.122**	0.097	0.867**	-0.377	-0.196
	(0.954)	(0.459)	(0.567)	(0.362)	(0.413)	(0.285)
MFA rate	-6,183*	-3,466	1,477	-798.8	6,311***	2,022
	(3,737)	(3,254)	(2,350)	(2,193)	(2,153)	(2,007)
Post * Chinese tariff	0.370	0.125	0.312	0.239	0.115	0.196
	(0.639)	(0.450)	(0.427)	(0.358)	(0.360)	(0.254)
Post * No College	0.038	0.010	0.084*	0.078*	-0.001	0.085***
	(0.063)	(0.046)	(0.046)	(0.042)	(0.030)	(0.031)
Post * Veteran	-0.004	0.091	-0.106	0.034	-0.087	-0.004
	(0.129)	(0.107)	(0.089)	(0.072)	(0.061)	(0.067)
Post * Median HHI	0.026	-0.042**	0.035*	0.029	0.005	0.064***
	(0.025)	(0.019)	(0.019)	(0.018)	(0.012)	(0.012)
Observations	5,394	5,398	5,397	5,401	5,396	5,399
R^2	0.174	0.143	0.326	0.213	0.215	0.180

Note. Standard errors clustered on MSAs in parentheses, MSA and year fixed effects.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

from Table 1.1, the service sector tends to employ more women. Hence, the more educated women tend to find jobs in the service sector. By the same logic, many of the less educated men seem to lose their jobs in the manufacturing sector. We conjecture that the less educated women in the manufacturing sector are less affected than the less educated men since their roles are different. Pierce and Schott (2016) show that US firms in sectors more exposed to trade liberalization introduced more labor-saving technologies. Less educated men are more affected since their roles may depend more on physical abilities. This is consistent with Juhn, Ujhelyi, and Villegas-Sanchez (2014) who show that NAFTA tariff reductions raised the relative wage of female workers in blue-collar tasks in Mexico. They explain that higher competition encouraged Mexican firms to modernize their technology and thus reduced their dependence on physical ability of workers. Changes we observe in how labor force participation rates are affected across different levels of education are consistent with our conjecture based on residual wage regression results. The increase in the observed relative female wage, coupled with higher residual wages for men, are due to the effect of China being granted PNTR status being stronger for the male labor market and inducing more women to join the labor force. A selection effect operated in the female labor market which favored the entry of more educated women. In the next section we investigate whether women entered the labor force in order to substitute the lost income from their partners leaving the labor force, voluntarily or involuntarily.

1.3.4 Intra-household Adjustments

China receiving PNTR status resulted in more women joining the labor force, while men became discouraged and left the labor force or left the more exposed MSAs, as shown by Greenland, Lopresti, and McHenry (2019). An interesting question we can ask is how intra-household employment dynamics were affected. If men become discouraged and do not move from their current MSA, the increase in female labor force participation may be indicative of women taking on a larger role of earning an income in households with married or cohabiting couples. We examine whether there are changes in the fraction of households with both spouses working, or just one spouse, either husband or wife working, estimating Equation 3.1 with the respective ratios as dependent variables. We restrict the sample to only those households with married or cohabiting couples. Our results are collected in Table 1.9.

From the first column, we can see that there does not seem to be a significant change in the fraction of households with both spouses working. At the same time, there is a significant reduction in the fraction of households with only the husband working and a significant increase in the fraction of households with only the wife working. These results should not necessarily be surprising. The reduction in labor force participation on the part of men as they become discouraged creates the need within households for women to play an increasingly important role in income generation. As a result, women enter the labor force in growing numbers to make up for the shortfall created by men leaving the labor force.

To further examine whether such intra-household adjustments took place we examine changes in the share of income earned by women in married or cohabiting households. To

Table 1.9: Intrahousehold work dynamics

	Working spouses			Share of female income in
	Both	Husband only	Wife only	household income
Post * NTR Gap	0.0455	-0.171*	0.148***	0.228*
	(0.205)	(0.102)	(0.0503)	(0.138)
NTR rate	0.772*	-0.386*	0.000165	0.433*
	(0.421)	(0.205)	(0.141)	(0.256)
MFA rate	3,467	-340.1	-1,393	-2,683*
	(2,601)	(1,290)	(1,030)	(1,430)
Post * Chinese tariff	0.0679	-0.241	0.207**	0.165
	(0.356)	(0.177)	(0.0983)	(0.202)
Post * No College	0.00503	-0.0202	0.0177*	0.0155
	(0.0334)	(0.0157)	(0.0102)	(0.0217)
Post * Veteran	-0.115*	-0.00393	0.0616***	0.00584
	(0.0665)	(0.0302)	(0.0195)	(0.0355)
Post * Median HHI	0.0509***	-0.0169***	-0.00854**	-0.00353
	(0.0122)	(0.00630)	(0.00408)	(0.00755)
Observations	5,401	5,401	5,401	5,398
R^2	0.351	0.316	0.223	0.239

Note. Standard errors clustered on MSAs in parentheses, MSA and year fixed effects.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

that end we estimate Equation 3.1 with all control variables and use the share of female income in household income as the dependent variable. Results are shown in the last column of Table 1.9. As we can see from the table, in MSAs that were more exposed to the effects of China receiving PNTR status, the female share of household income did increase.

Our results contrast with Keller and Utar (2018). They show that lower labor market opportunity due to the growing Chinese import competition raised gender inequality in Denmark by inducing female workers to stay away from the labor market (more parental leave, higher fertility, more marriage, and fewer divorces). The different outcomes may be explained by Denmark's better social safety net or the more flexible labor market in the US. If the latter is the main reason, the change in female labor force participation may not depend on marital status. Table 1.10 reports the impact of PNTR with China on labor force participation rate changes in our sample for males and females with different marital status. This table shows that labor force participation rate of females in married or cohabiting households significantly increased while those in single households were not significantly affected, supporting the claim that women entered the labor force to replace the lost income from their male partners' leaving the labor force. While the effect on married male labor force participation rates is not statistically significant, it is estimated with a negative sign, which is in line with the substitution hypothesis.

Table 1.10: Labor force participation rate by marital status

	Single households		Married or cohabiting household	
	Male LFPR	Female LFPR	Male LFPR	Female LFPR
Post * NTR Gap	-0.335*	0.207	-0.152	0.458**
	(0.183)	(0.237)	(0.107)	(0.222)
NTR rate	-0.696	-0.110	0.0933	1.276***
	(0.434)	(0.456)	(0.260)	(0.399)
MFA rate	4,969*	2,655	2,525	1,014
	(2,668)	(2,921)	(1,890)	(2,309)
Post * Chinese tariff	0.172	-0.0119	0.224	0.476
	(0.348)	(0.397)	(0.201)	(0.408)
Post * No College	0.0430	-0.00268	0.0350*	0.0804*
	(0.0377)	(0.0380)	(0.0197)	(0.0444)
Post * Veteran	-0.154**	-0.0245	-0.0409	-0.0432
	(0.0780)	(0.0766)	(0.0466)	(0.0752)
Post * Median HHI	0.0231*	0.0250*	0.0321***	0.0437**
	(0.0131)	(0.0150)	(0.00854)	(0.0191)
Observations	5,386	5,395	5,400	5,401
R^2	0.179	0.234	0.215	0.359

Note. Standard errors clustered on MSAs in parentheses, MSA and year fixed effects.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

1.3.5 Other Changes in Local Labor Markets

Our approach precludes us from drawing welfare implications due to both modeling and data limitations. However, we can take advantage of additional data to better understand the driving forces behind the increased labor force participation of women and decreased participation of men. Labor force participation numbers reflect both individuals who are working and those who are not working but are actively seeking employment. Thus, increases in labor force participation could come from the ranks of the officially unemployed: those actively seeking employment. The other possibility is that even if the increase in labor force participation comes from more individuals working, it is not clear whether the increase comes from individuals holding full- or part-time jobs. Granting China PNTR status may have resulted in a redistribution of jobs from full- to part-time employment, which would be indicative of structural changes in local labor markets which were more exposed to the shock.

Table 1.11: Unemployment and employment rates

	Unemployment rate		Employment rate	
	Female	Male	Female	Male
Post * NTR Gap	0.231***	0.168*	0.197	-0.347**
	(0.0742)	(0.0997)	(0.180)	(0.144)
NTR rate	-0.134	-0.210	0.780***	0.0665
	(0.262)	(0.260)	(0.291)	(0.300)
MFA rate	-1,536	-1,798	2,360	5,527***
	(1,034)	(1,143)	(1,601)	(1,903)
Post * Chinese tariff	0.143	0.0432	0.222	0.162
	(0.145)	(0.189)	(0.312)	(0.249)
Post * No College	0.00373	0.0159	0.0475	0.0184
	(0.0157)	(0.0162)	(0.0353)	(0.0233)
Post * Veteran	-0.0208	0.0430	-0.0172	-0.0948**
	(0.0299)	(0.0317)	(0.0570)	(0.0453)
Post * Median HHI	-0.0266***	-0.0171**	0.0504***	0.0455***
	(0.00706)	(0.00711)	(0.0149)	(0.0100)
Observations	5,400	5,400	5,401	5,400
R^2	0.259	0.320	0.458	0.368

Note. Standard errors clustered on MSAs in parentheses, MSA and year fixed effects.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

We begin by examining how unemployment and employment for both female and male workers have changed because of China being granted permanent normal trade relations with the US. Our results, collected in Table 1.11, show that unemployment rates for both female and male workers rose. The last two columns of Table 1.11 indicate that the employment rate of men decreased in MSAs with greater exposure while the female employment rate was not significantly affected. Taken together, these changes imply that much of the increase in the female labor force participation comes from more women joining the labor force and searching for jobs. Since our data do not allow us to track individuals across time, we cannot decompose net changes in labor force participation into its separate constituents. In other words, understanding how many women who join the labor force due to China receiving PNTR status are unable to find jobs, but keep looking for one, is beyond our scope. For men, the conclusion is clear cut. Male unemployment rate increases, while their employment rate decreases. Both changes have likely resulted in some men becoming discouraged and dropping out of the labor force or moving out of the MSA, the latter being consistent with the findings of Greenland, Lopresti, and McHenry (2019).

Table 1.12: Total hours worked and part-time work

	Total hours worked (log value)		Weeks in part-time work (log value)	
	Female	Male	Female	Male
Post * NTR Gap	-0.188	-0.409***	2.597*	2.440
	(0.172)	(0.148)	(1.333)	(1.747)
NTR rate	0.470	-0.286	2.076	0.607
	(0.393)	(0.296)	(1.848)	(3.624)
MFA rate	806.9	3,017*	-2,653	-26,460
	(1,630)	(1,739)	(17,361)	(21,831)
Post * Chinese tariff	0.0438	0.00605	0.993	-0.368
	(0.310)	(0.248)	(2.037)	(3.046)
Post * No College	0.0320	0.00845	-0.191	0.0892
	(0.0272)	(0.0225)	(0.188)	(0.318)
Post * Veteran	-0.0336	0.0675	-0.532	0.700
	(0.0477)	(0.0499)	(0.393)	(0.632)
Post * Median HHI	0.00687	0.0207**	-0.0247	0.0697
	(0.0107)	(0.00914)	(0.0719)	(0.107)
Observations	5,358	5,357	5,348	5,249
R^2	0.299	0.296	0.275	0.175

Note. Standard errors clustered on MSAs in parentheses, MSA and year fixed effects.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

To examine the kinds of jobs individuals in our sample hold, we take advantage of two additional variables, total hours worked and weeks spent in part-time employment. The former reflects the number of hours spent working in both full- and part-time jobs in a calendar year, while the latter reflects the number of weeks individuals spent in part-time employment, defined as working less than 35 hours a week. We estimate Equation 3.1 with total hours worked and weeks in part-time employment as dependent variables collecting our results in Table 1.12. While our results indicate that both men and women spend less time working after China is granted PNTR, only for men is the coefficient estimated precisely.

Similarly, while our results indicate both men and women spent more time in part-time employment, only the coefficient for women is estimated precisely. Taken together, these results indicate that both men and women experience a change in the fundamental nature of jobs they held, facing limited opportunities for full-time work and greater reliance on part-time work.

Table 1.13: Reasons for part-time work

	Cannot find a full-time job		WWanted a part-time job	
	Female	Male	Female	Male
Post * NTR Gap	0.573**	0.537*	-0.663	0.270
	(0.251)	(0.310)	(0.464)	(0.389)
NTR rate	-0.328	0.135	0.479	0.168
	(0.449)	(0.655)	(0.985)	(0.833)
MFA rate	602.4	-3,472	4,242	10,070
	(3,375)	(3,294)	(5,308)	(6,567)
Post * Chinese tariff	0.319	-0.576	-1.895**	0.463
	(0.424)	(0.551)	(0.768)	(0.647)
Post * No College	0.065	-0.005	-0.026	0.031
	(0.041)	(0.051)	(0.071)	(0.074)
Post * Veteran	-0.129	0.047	0.390***	-0.072
	(0.080)	(0.110)	(0.118)	(0.124)
Post * Median HHI	-0.020	0.001	0.025	-0.004
	(0.017)	(0.022)	(0.024)	(0.026)
Observations	5,348	5,249	5,348	5,249
R^2	0.177	0.125	0.235	0.147

Note. Standard errors clustered on MSAs in parentheses, MSA and year fixed effects.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

To better understand whether the nature of jobs held changed because individuals started preferring part- to full-time employment, we take advantage of our data asking respondents to identify the reasons behind their working a part-time job focusing on two of them: whether they reported being unable to find a full-time job and whether they reported preferring a part-time job. We then estimate Equation 3.1 with the proportion of individuals who could not find full-time employment and then the proportion who wanted part-time employment,[12] separately for women and men, collecting our results in Table 1.13. During

[12]The denominator for both measures is the number of individuals in each gender group who held a part-time job in the previous year.

our sample, there is no significant change in the proportion of either women or men who want part-time work. However, granting China PNTR status is associated with a large and statistically significant increase in the proportion of both women and men who state that they were unable to find full-time employment and settled for part-time work instead. Thus, the change in the nature of jobs occurred due to labor market conditions and increased exposure to import competition from China, rather than due to changes in preferences.

1.4 Robustness

We conduct several robustness exercises. The first one replicates the two exogeneity robustness checks of Pierce and Schott (2016). The use of NTR gap to identify the effect of granting China PNTR status relies on the exogeneity of the NTR gap. As Pierce and Schott (2016) argue, most of the variation in NTR gap is due to the variation in non-NTR tariff rates which were set in 1930 and any increase in NTR to protect industries would result in a smaller NTR gap. They perform two checks of exogeneity of NTR gap. One was to instrument the baseline DD term, $PostPNTR_t \times NTRGap_m$, with an interaction of the post-PNTR indicator and the Smoot-Hawley-based non-NTR tariffs rates, $PostPNTR_t \times non-NTRTariff_j$. The second one was to re-estimate the baseline specification using the NTR gap observed in 1990, ten years prior to PNTR implementation.

The second robustness exercise adds several additional explanatory variables to our benchmark regressions. We interact the share of foreign-born individuals with the Post PNTR indicator since a larger immigrant population may be associated with higher labor force participation among higher-skilled workers (Peri, 2014). We control for the MSA's share of employment in routine occupations given that areas exposed to import competition are also more susceptible to worker displacement by automation. We add the share of employment in manufacturing in an MSA interacted with a Post PNTR indicator as manufacturing jobs are at greatest risk according to Pierce and Schott (2016). Finally, we add the average offshorability index to control for the exposure to offshorability of jobs for an

MSA (Autor, Dorn, and Hanson, 2013).

Table 1.14: Robustness checks

	Benchmark	2000 NTR Gap	NNTR IV	Additional variables
female wage/male wage	0.678**	0.595*	0.596**	2.192*
female wage	0.597*	0.582	0.579**	1.192*
male wage	-0.206	-0.115	-0.117	-0.145
female LFPR/male LFPR	0.671***	0.617***	0.629***	0.673***
female LFPR	0.395**	0.352**	0.356***	0.404**
male LFPR	-0.206**	-0.207**	-0.214**	-0.180*

Note. Standard errors clustered on MSAs in parentheses, MSA and year fixed effects.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

In the interest of space, we present only the estimates of the DD term, $PostPNTR_t \times NTRGap_m$, in regressions involving the wage and labor-force-participation gaps, as well as for gender-specific wage and labor force participation rates in Table 1.14.[13] Across all three robustness checks, our results are qualitatively similar. Robustness results for wage related regressions are the least precisely estimated. In each regression, the wage gap decreases in the most exposed MSAs, while the male wage decreases and the female wage increases. In all three robustness checks the gender labor-force-participation gap decreases in the most exposed MSAs, with similar magnitudes across all regressions and is precisely estimated. Female labor force participation in the more exposed MSAs is also precisely estimated to increase by a similar magnitude across all regressions. Male labor force participation is decreasing by a similar magnitude in all regressions and is precisely estimated. Thus, our robustness results confirm our main conclusions: the gender wage gap and the gender labor-force-participation gap both decrease in the wake of China receiving PNTR status, with the labor force participation results more precisely estimated. The last robustness check we perform is to examine to what extent our results are affected by the Great Recession which started in 2008. To that end we add a new variable to our regression specification given by Equation 3.1 which is the interaction of the $PostPNTR_t \times NTRGap_m$ variable and a dummy variable identifying the 2008 through 2013 period. In Table 1.15

[13] Complete results are available on request.

we only present the estimated coefficients for the $PostPNTR_t \times NTRGap_m$ term and the new triple interaction term to identify what effect the Great Recession had for the four key regressions, simple wage gap in the full and Machado sample, residual wage gap, and labor force participation gap.[14] As can be seen, the simple wage gender gap decreased prior to the Great Recession which had no statistically significant effect on it. The results for the Machado sample indicate that there is no change in the wage gap prior to the Great Recession, but the Great Recession had a large effect on the wage gap decreasing it in the post-2008 period. The residual wage regression indicates that the residual wage gap increased prior to the Great Recession, which had no additional effect on the residual wage gap. The results for the simple wage gap in the Machado sample taken together with the residual wage regression results indicate that there was important selection effect in the post-PNTR period and prior to the Great Recession as discussed earlier in the chapter. Finally, in terms of the labor force participation gender gap, the gap decreased prior to the Great Recession, which decreased it further by roughly a similar amount.

Table 1.15: Wage and labor force participation rate gap and the Great Recession

	Full Sample	Machado Sample	Residual Wage†	LFPR
Post * NTR Gap	0.671*	0.154	0.189***	0.480**
	(0.379)	(0.933)	(0.066)	(0.192)
Post * NTR Gap * (2008-13 Dummy)	0.114	3.111**	-0.007	0.445**
	(0.394)	(1.402)	(0.032)	(0.225)

Note. †The independent variable reported for the residual wage regression are $PostPNTR_t \times NTRGap_m \times MaleDummy$ and $PostNTR_t \times NTRGap_m \times MaleDummy \times (2008 - 13Dummy)$.
Standard errors clustered on MSAs in parentheses, MSA and year fixed effects.
*** p $<$ 0.01, ** p $<$ 0.05, * p $<$ 0.1

[14]The residual wage regression is the exception as the dependent variable of interest here is the male wage in the post-2001 period interacted with NTR Gap, the triple-difference term. Therefore, the additional independent variable is the interaction between that variable and a dummy identifying the 2008-2013 period.

1.5 Conclusion

China being granted PNTR status caused several important changes in local labor markets. Gender wage and labor-force-participation gaps both declined. We show that the simple gender wage gap decreased, but that there were also important selection effects in the wake of the PNTR change. Our residual wage regression shows that the male residual wage increased which is indicative of increased quality of the male labor force. Our results further show that less educated men left the labor force in greater numbers and that more educated women entered the labor force in greater numbers, both of which help explain the residual wage gap result. As a result of both of these forces, the gender gap in labor force participation decreased in the most exposed MSAs due to more women joining the labor force, while men became discouraged and left the labor force. These changes were accompanied by increased unemployment among women and men, while the employment rate of women did not change and that of men decreased. Concurrently, both women and men spent less overall time working. While the reduction in time spent working for women is imprecisely estimated, women did spend more time in part-time employment indicating a reduction in full-time work. Our results indicate both women and men spent more time in part-time work because they were unable to find full-time employment, rather than because they preferred part-time employment. This episode induced changes in intrahousehold work dynamics. While there were no changes in the number of households where both spouses worked, in the more exposed MSAs there was a decrease in the households with just the husband working and an increase in the households with only the wife working. In addition, the share of family income accounted for by the female partner increased in the more exposed MSAs. We show that labor force participation rates increased among married women, while those of single women did not change. Thus, our results indicate that women entered the labor force to replace the lost family income due to husbands leaving the labor force or becoming unemployed.

Lower gender gaps in labor markets are often interpreted as female welfare improvement. However, if a negative shock in the labor market affected male workers more severely or forced more females to work as shown by this chapter, this conclusion would be too hasty. While it is tempting to use our results to form conclusions about welfare implications, our approach and data limitations preclude us from doing so and are left for future work.

CHAPTER 2

DOES MINIMUM WAGE INCREASE OR REDUCE CRIME? EVIDENCE FROM A NEGATIVE INCOME SHOCK

2.1 Introduction

There is a common conception that irregularities in the business cycle lead to higher crime rates. The US officially granted Permanent Normal Trade Relations (PNTR) to China upon its accession to the World Trade Organization (WTO) at the end of 2001. This episode, commonly known as the China Shock, has brought dramatic changes to the US labor market and is extensively studied in the literature. The economic hardship further brought mental/psychological frustration to the people who used to work in the manufacturing sectors in the US due to a loss of disposable income (Kim, 2018; Pierce and Schott, 2016; Autor, Dorn, and Hanson, 2016; Caliendo, Dvorkin, and Parro, 2019b). Exposed workers experienced reduced lifetime income and depressed wage levels for at least a full decade after the China Shock commenced (Autor, Dorn, and Hanson, 2016). The standard of living for most fell considerably, which put tremendous pressure on maintaining their accustomed lifestyle. This negative income shock is believed to have caused a significant increase in crime rates in US counties that have higher exposures to the China Shock (Pierce and Schott, 2016).

Increasing incarceration and police can be an effective (Levitt, 2004; Corman and Mocan, 2005; Chalfin and McCrary, 2018; Fone, Sabia, and Cesur, 2019) but expensive policy strategy (Kearney et al., 2014) to reduce crime rates. Expenditures on police and the criminal justice system are estimated to be more than $286 billion per year (Bureau Of Justice Statistics, 2018). Executive Office of the President (2016)[1] from the White House Council

[1]This report claimed that raising the federal minimum wage from $7.25 to $12 per hour could reduce crime by 3 to 5 percent, generating substantial social benefits.

of Economic Advisers contrasted the high public costs of deterring crime via the criminal justice system with lower-cost alternatives. It recommended a novel policy strategy for combating crime: raising the minimum wage. Subsequently, on July 18, 2019, the House passed the Raise the Wage Act to increase the federal minimum wage from $7.25 to $15 by 2024 and index future increases to median wage growth and eliminate the sub-minimum wage for tipped workers, teenage workers, and individuals with disabilities.[2]

This chapter answers two questions empirically: 1) Did the China Shock increase crime rates in the US, and 2) would higher state-level minimum wage help alleviate this impact? The role of the minimum wage on crime rates is usually hard to estimate under a typical environment. In this chapter, we employ a negative income shock - the China Shock - to investigate this relationship. Specifically, we exploit the measure of different trade exposures to Chinese imports in commuting zones, and there are two steps to the analysis. First, we study the link between PNTR and crime rates, which provides evidence that PNTR brought labor market disruptions. We estimate the China Shock's impact on property crime and violent crime, and the breakdown of these crimes within gender, age, and racial groups. Second, we examine the role of minimum wage on local crime rates in the presence of the China Shock to see if it played a role in keeping people away from criminal activities.

Following Pierce and Schott (2016), we adopt the measure of trade exposure of local communities as the Normal Trade Relation (NTR) gap at the commuting zone (CZ) level. NTR gap - the difference between non-NTR tariff rates and NTR tariff rates - effectively captures the amount of uncertainty of a trade policy change that a CZ faced. After China's accession into WTO in 2001, the NTR gap was reduced to zero. This sudden drop serves as an ideal exogenous shock of a trade policy change in 2001. The higher the NTR gap, the CZ experienced more labor market disruptions due to trade liberalization with China.

We use data from the Uniform Crime Reports (UCR) of the National Incident-Based Reporting System from the Federal Bureau of Investigation, with years ranging from 1990

[2]An alternative set of policies to deter crime, which are often less costly to taxpayers, includes those that improve labor market conditions and incentivize greater human capital acquisition.

to 2013. We compute an index of overall property crimes[3] and overall violent crimes,[4] both of which are normalized per 1,000 residents in a CZ. We also calculate the breakdown of crime rates by gender, age, and racial groups.

As the baseline estimation, we use the difference-in-difference (DD) identification strategy to examine whether CZs that are more exposed to Chinese import competition (first difference) experienced differential changes in crime rates after the China Shock (second difference). The specification includes controls for CZ-level demographic and economic attributes, as well as fixed effects that capture time-invariant characteristics of CZs and aggregate shocks that affect all CZs in a particular year.

The baseline results confirm that the China shock indeed statistically significantly increased overall property crimes, while it had no effect on violent crimes. Specifically, the China Shock induced an estimated $10,151 more in social costs from an 8.4 percent increase in property crimes for an interquartile change in trade exposures across CZs. The results are consistent with our expectation since property crimes are usually tied to financial needs and motives. As increased import competition from China caused the loss of disposable income and job-loss induced idleness among manufacturing workers, they may commit property crimes due to monetary concerns. Those without a steady income have a greater incentive to commit crimes than those with a steady income, who may have more to lose if caught (Ajimotokin, Haskins, and Wade, 2015). Specifically, we find the magnitude of this effect is unusually large for young adults (age 20-29). The implied impact shows young adults in CZs heavily impacted by the China Shock (75th percentile in NTR gap distribution) committed 1.82 times more property crimes than those in less-impacted CZs (25th percentile in NTR gap distribution). Moreover, the overall property crimes from both male and female perpetrators increased. In terms of race, results show that people identified as white, Asian, and American Indians all committed significantly more property crimes. People identified as black committed more violent crimes. These findings are consistent

[3]Summation of burglary, theft, motor vehicle theft, and arson.

[4]Summation of murder, rape, robbery, and aggravated assault.

with Stolzenberg, Eitle, and D'alessio (2006) and Pierce and Schott (2020).

In the second part of the chapter, we further explore if higher state-level minimum wages had a dampening effect on overall CZ-level crime rates. We estimate a difference-in-difference-in-difference (DDD) specification. The results show that higher state-level minimum wages had a significant dampening effect on overall property crimes, resulting in less property crime in the more exposed areas due to the China Shock. Its impact is significant across all sub-categories of property crimes - burglary, theft, motor vehicle theft, and arson. This effect corresponds to a reduction in social costs of \$ 34,823, \$ 1,475, \$ 1,546, \$ 1,748, and \$ 234 respectively for an interquartile shift in the minimum wage distribution. Moreover, higher minimum wages reduced property crimes committed by young adults the most in terms of magnitude. In general, a one-dollar increase in the federal-level minimum wage witnessed a 22 percent decrease in property crimes committed by young adults across all CZs. Young adults, typically characterized as vulnerable workers, are usually low-skilled workers who are paid the minimum wage. Thus, higher minimum wages may bring young workers to the legitimate labor market, resulting in fewer potential property crime perpetrators. Furthermore, we find that higher minimum wages reduced overall property crime and overall violent crime from both male and female perpetrators. In terms of racial groups, higher minimum wages decreased property crime committed by whites. We do not find a significant impact of social welfare spending. The results consolidate the claim that a higher level minimum wage plays a significant role in reducing crime rates due to the China Shock.

We examine the robustness of these results in two ways. First, we consider the possibility that pre-existing trends could drive the results by employing an alternate empirical specification that places no restrictions on the timing of any potential decreases in the crime rate. Second, we account for the concurrent opioid epidemic that may lead to spurious crime rate increases by including state-level opioid regulation with the full set of year dummies in the regression. The results sustain for both of these two robustness checks.

In the final part of the chapter, we present evidence supporting labor market disruption as a plausible mechanism for minimum wages' impact on crime rates in the China Shock's presence. We employ the unemployment rate as the measure of job availability and two types of disability measures - total disability payments and the number of disabled workers - to examine potential mechanisms through the labor market. Results show the China Shock brought a significant increase in the unemployment rate and disability transfers. A higher level of minimum wages drew vulnerable workers back to the legitimate labor market, reducing their reliance on Disability Insurance and Supplemental Security Income, as well as potential substance abuse, which ultimately leads to crime rate reduction.

2.1.1 Related Literature

This research differs from the literature that examined the link between minimum wage and crime and highlights three key innovations. First, we incorporate a negative income shock to study the association between minimum wage and crime. By doing this, we can identify whether higher minimum wage reduces crime rates, especially during times of financial/income crisis. Second, we measure the China Shock's impact on the commuting zone level, which clusters US counties characterized by strong within-cluster and weak between-cluster commuting ties. It provides a local labor market geography that covers the entire land area of the United States. Third, this study accounts for social welfare spending, another policy tool to reduce crime rates, to separately identify the impact of minimum wages from the general social safety net.

This study contributes to the literature in trade and labor economics in several ways. The literature that examines the relationship between minimum wage and crime is recent and small. The previous studies in labor economics provide some potential channels of influence. Becker's theory of rational crime (Becker, 1968) posits that criminal behavior is responsive to labor market conditions and human capital acquisition. Criminal behavior is negatively related to employment opportunities (Mustard, 2010; Schnepel, 2018), wages (Gould, Weinberg, and Mustard, 2002; Yang, 2017), and educational attainment (Machin and Meghir, 2004; Anderson, 2014). For example, lack of employment opportunities, as found in Nordin and Almén (2017), such as minimum-wage-induced job loss or hours reductions may lead to more property crime for economic reasons, and more violent crime for despair-related, emotionally expressive reasons. Hashimoto (1982) found negative impacts of higher minimum wage on young workers by reducing their job training opportunity. Neumark and Nizalova (2007) examined the exposure to minimum wages at young ages could lead to adverse long-run effects via decreased labor market experience and tenure, and diminished education and training, while beneficial long-run effects could arise if minimum wages increase skill acquisition.

This chapter incorporates a discussion of negative income shock as a method for identifying the relationship between minimum wage and crime. The existing literature found the China Shock induced a robust negative income effect. Brussevich (2018) found wage and welfare losses of male workers in the manufacturing sector for a CZ hit by the China Shock due to heterogeneous switching costs between industries.

Other studies investigated the link between minimum wages and crimes. Besedeš, Lee, and Yang (2021) showed the China Shock contributed to a decline in male wages in the manufacturing and service sectors. Results also indicated that women entered the labor force to replace the lost family income due to husbands leaving the labor force or becoming unemployed. Hansen and Machin (2002)'s paper provided an empirical evaluation of whether one can uncover a link between crime and the labor market variables using a research methodology that is different from that utilized in existing work. They exploited a massive regulatory change made to the UK labor market when a national minimum wage was introduced in April 1999. Contrary to their research, we uncover a statistically significant negative relationship, showing relative crime reductions in areas that initially had more low wage workers. In a relevant recent research, Fone, Sabia, and Cesur (2019) argued that a higher minimum wage raised overall property crime rates for the young age group. Different from this research, they looked at correlations between minimum wage changes and crime rates, while in this chapter, we examine the role of minimum wage against a negative income shock. Additionally, we provide important insights on the role of minimum wage in current discussions.

As a policy tool targeted towards low-skilled workers, the minimum wage is often subject to a debate of whether it is a substitute for or a complement to expenditure oriented social welfare policies. Among those, social welfare spending is considered as an effective tool to reduce crime in a large body of theoretical empirical research (Fender, 1999; Fishback, Johnson, and Kantor, 2010; Chioda, De Mello, and Soares, 2016; Loureiro, 2012). These studies argued that social safety net programs reduced crime via channels such as supplemental security income, job training, and housing assistance help, which alleviated distress by providing work and income opportunities for the unemployed. This study disentangles the effect of minimum wages from social welfare spending by incorporating social welfare spending in the identification strategy. Therefore, we can separately identify the impact of minimum wage from the general social safety net while comparing their impacts on crime rates under a negative income shock.

This research builds on trade literature and adds to the growing research that studies the impacts of trade liberalization on multiple US socio-economic aspects. We employ Pierce and Schott's (2016) approach to measure a local labor market's exposure to trade liberalization. This chapter showed that granting PNTR to China in 2001 caused a sharp decline in US manufacturing employment in the 2000s. In a follow-up paper, Pierce and Schott (2020) calculated the exposure level to PNTR for each US county. They showed that a county's higher exposure to PNTR was associated with increases in mortality from stress-related causes, specifically among white males, and an increase in property crimes.[5] Other studies found significant trade liberalization effects on labor market outcomes and crime rates using different methodologies. Autor, Dorn, and Hanson (2013) explained the

[5]Similar research that examine the relationship between the China Shock and crime rates are found in Feler and Senses (2017a) and Che, Xu, and Zhang (2018).

decline in US manufacturing employment with Chinese import penetration. Their estimation strategy, to instrument the growth of Chinese exports to the US by the growth of Chinese exports to other high-income countries, was adopted by several follow-up papers. Caliendo, Dvorkin, and Parro (2019a) found a positive impact of the China Shock, which lowered the price level, but the effects were heterogeneous across regions due to moving frictions. Feler and Senses (2017b) found similar results that the China Shock lowered housing prices, leading to decreases in the quality of public goods. Greenland and Lopresti (2016) investigated the human capital aspect of the China Shock: higher CZ's exposure to the China Shock led to high school graduation rates increases. Greenland, Lopresti, and McHenry (2019) estimated population change. Higher CZ's exposure to the China Shock led to slower population growth, especially for the young age and low education individuals. Similarly, Feenstra, Xu, and Ma (2019) and Byun and Lee (2019) investigated China Shock's mitigation effects through the housing market and the local banking system.

The remainder of this chapter proceeds as follows. Section 2.2 discusses the background and the data used for the analysis. Section 2.3 presents the models and identification strategy, followed by Section 2.4, discussing the estimation results. Section 2.5 discusses the robustness of the results. Section 2.6 investigates potential mechanisms and Section 2.7 concludes.

2.2 Background and Data

2.2.1 Background

In the past thirty-five years, China jumped from being an insignificant contributor to world GDP to the second-largest economy and the largest trading country. In 2007, China became the US' largest import source, accounting for 17 percent of all imports versus just 3 percent in 1990. As indicated in Pierce and Schott (2016), the US' growing imports from China coincide with a sharp, 18 percent decline in US manufacturing employment from 2001 to 2007, with more than 80 percent of the decline occurring between 2001 and 2004. This decline was steeper in industries more exposed to the US granting permanent normal trade relations to China. Exposed workers experienced reduced lifetime income and depressed wage levels for at least a full decade after the China Shock occurred (Autor, Dorn, and Hanson, 2016).

The US operates two tariff systems depending on the status given to its trading partner. Countries with Normal Trade Relations (NTR) status are eligible to receive low tariff rates (NTR rates), which are reserved for members of the WTO. The NTR rates are significantly lower than tariff rates for countries without NTR status (non-NTR rates) by, on average, around 30 percentage points. The non-NTR rates are often applied to non-market-economy countries. Although China's status had been a non-market economy, US imports from China had been subject to the NTR rates since 1980. China's NTR status was temporary in the sense that such NTR status required renewal by the US Congress on an annual basis. The renewal had continued successively on a year-over-year term, although the success of the annual renewal procedure was highly uncertain ex-ante for market participants, including US importers and Chinese exporters. Simply put, high uncertainty was a major obstacle to long-term investment in China. Hence, the bill's passage granting Permanent Normal Trade Relation (PNTR) status to China in October 2000 eliminated the uncertainty for potential tariff hikes.[6]

Pierce and Schott (2016) quantify an industry-level exposure to the imposition of PNTR ($NTRGap_j$) as a difference between the non-NTR rate and the NTR rate;

$$NTRGap_j = non - NTR\, tariff_j - NTR\, tariff_j, \tag{2.1}$$

which captures a degree of the trade uncertainty that firms within an industry would have faced prior to the bill's passage. Given industry-level exposure, Pierce and Schott (2020) suggest a county-level exposure to the China Shock by using a county's employment shares across industries. Following their approach, we construct a CZ-level exposure ($NTRGap_c$)

[6] In this chapter, we use the year 2001 to characterize pre-PNTR period and post-PNTR period.

to the China Shock;

$$NTRGap_c = \sum_j \frac{L_{j,c}}{L_c} \times NTRGap_j, \tag{2.2}$$

where $L_{j,c}$ refers to the number of employees for an industry j at a commuting zone c and L_c refers to the total number of employees for a commuting zone c in the year 1990.[7] Figure 2.1 reports geographical distribution of $NTRGap_c$.

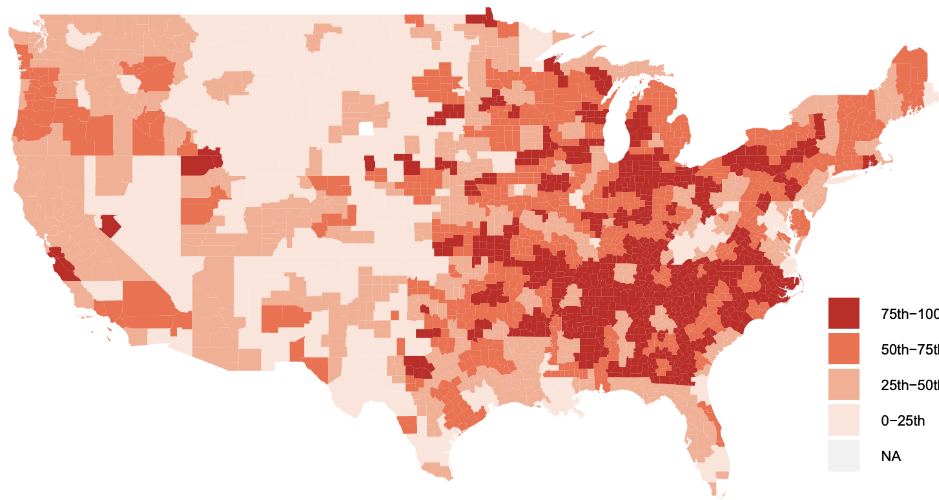


Figure 2.1: Number of arrests per 1,000 residents by commuting zone in 2000

2.2.2 Data

The crime data comes from Uniform Crime Reports (UCR) of the National Incident-Based Reporting System from the Federal Bureau of Investigation, 1990-2013. We use the data organized by Kaplan (2018), which provides the annual number of arrests at the law-enforcement-agency level and we aggregate the number of arrests at the CZ level. Following UCR's crime categories, Kaplan classifies each crime into two main categories,

[7] We use the US Department of Agriculture definition of commuting zones as of 1990 and the concordance of counties in commuting zones provided by Autor, Dorn, and Hanson (2013). The employment information is obtained from County Business Patterns (CBP) provided by U.S. Census Bureau (1990-2013b). Regarding the missing observations for a few industries in the CBP dataset, we impute those values following Autor, Dorn, and Hanson (2013), which also provides codes to aggregate employment.

property crime and violent crime, and four sub-categories for each: burglary, theft, motor vehicle theft, arson; and murder, rape, robbery, aggravated assault.[8] The number of arrests is also separately reported by the offender's demographics such as age, sex, and race. The main focus of this chapter is on the differential impacts on five age groups: under 20, 20-29, 30-39, 40-49, and over 49 years old. We normalize the number of arrests using the population for each age group provided by U.S. Census Bureau (2015), and derive the number of arrests per 1,000 individuals for each CZ $\times$ year $\times$ crime type, which builds the dependent variables.

Figure A.2 plots the distributions of overall property crime and violent crime rates across CZs in 1990, 2007, 2010, and 2013. The figure shows that the support of property crime is relatively wider than that of violent crime and that property crime rates vary substantially across CZs. This pattern can be confirmed from Table 2.1. It reports the summary statistics of property crime and violent crime, and the breakdown of them by demographic groups of gender, age, and race. The statistics show that overall, property crime rates are higher than violent crime rates. Males in general committed more crimes than females. Young adults aged 20-29 are more likely to commit crimes, and the likelihood to commit crimes is decreasing as age increases. Moreover, black crime perpetrators are larger than other racial groups, in terms of both property crime and violent crime.

We use the state-level minimum wage in the year 2000, one year before the China Shock. In the case that the state-level minimum wage was higher than the federal-level minimum wage, we assign a CZ minimum wage of the state that it belongs to.[9] We collect the federal and state-level minimum wages from the US Department of Labor. To separate the impact of minimum wage from the general social safety net, we control for social welfare spending per capita of the state where a CZ is located. Following $II-1$ in De-

[8] Table A.1 shows the CZs with the highest and lowest NTR Gaps, and Figure A.1 shows geographic distributions of overall property crimes and overall violent crimes in 2000. The overall property crime refer to the summation of burglary, theft, motor vehicle theft, and arson; similarly the overall violent crime refer to the summation of murder, rape, robbery, and aggravated assault.

[9] We are aware that there are 46 cities and 6 counties have local ordinances. However, in 2000, all of the local ordinances are lower than the state level. All CZs are subsets of a state.

Table 2.1: Summary statistics of crime rates, 1990-2013

(a) By All and Gender

	All	Male	Female
Property Crime	0.004 (0.004)	6.48 (5.39)	2.6 (2.47)
Burglary	0.001 (0.001)	1.57 (1.24)	0.19 (0.21)
Theft	0.003 (0.003)	2.3 (2.25)	2.77 (2.53)
Motor Vehicle Theft	0 (0.001)	0.49 (0.64)	0.1 (0.43)
Arson	0 (0)	0.08 (0.16)	0.01 (0.05)
Violent Crime	0.001 (0.001)	2.16 (1.92)	0.4 (0.44)
Murder	0 (0)	0.06 (0.09)	0.01 (0.02)
Rape	0 (0)	0.15 (0.17)	0 (0.01)
Robbery	0 (0)	0.29 (0.36)	0.03 (0.05)
Aggravated Assault	0.001 (0.001)	1.66 (1.61)	0.36 (0.41)

(b) By age

	Under 20	20-29	30-39	40-49	Over 40
Property Crime	7.06 (6.18)	9.57 (10.83)	5.1 (4.85)	2.8 (5.85)	0.64 (0.55)
Burglary	1.5 (1.4)	2.04 (1.92)	0.89 (0.92)	0.39 (0.46)	0.05 (0.08)
Theft	4.94 (4.31)	6.8 (9.93)	3.87 (4.22)	2.25 (5.72)	0.56 (0.5)
Motor Vehicle Theft	0.52 (1.64)	0.64 (0.88)	0.3 (0.42)	0.13 (0.23)	0.02 (0.05)
Arson	0.09 (0.18)	0.08 (0.27)	0.05 (0.17)	0.03 (0.13)	0.01 (0.03)
Violent Crime	1.02 (0.95)	3.49 (3.22)	2.14 (2.11)	1.18 (2.12)	0.26 (0.32)
Murder	0.02 (0.05)	0.1 (0.2)	0.05 (0.12)	0.03 (0.13)	0.01 (0.03)
Rape	0.07 (0.11)	0.21 (0.33)	0.12 (0.19)	0.06 (0.14)	0.02 (0.05)
Robbery	0.21 (0.29)	0.44 (0.57)	0.19 (0.27)	0.08 (0.13)	0.01 (0.03)
Aggravated Assault	0.72 (0.71)	2.75 (2.78)	1.78 (1.91)	1.01 (2.06)	0.22 (0.3)

(c) By race

	White	Asian	Black	American Indian
Property Crime	3.81 (3.03)	3.7 (32.93)	17.56 (53.32)	5.72 (23.01)
Burglary	0.75 (0.61)	0.55 (10.66)	3.08 (21.27)	1.07 (10.05)
Theft	2.77 (2.53)	2.79 (29.28)	12.67 (38.48)	3.89 (11.02)
Motor Vehicle Theft	0.24 (0.27)	0.33 (8.6)	1.68 (17.9)	0.65 (8.78)
Arson	0.04 (0.09)	0.03 (1.05)	0.14 (2.16)	0.11 (7.61)
Violent Crime	0.96 (0.93)	0.79 (8.52)	6.42 (23.76)	1.63 (12.29)
Murder	0.02 (0.04)	0.03 (0.9)	0.15 (2.66)	0.04 (0.43)
Rape	0.06 (0.09)	0.06 (1)	0.54 (6.57)	0.09 (0.94)
Robbery	0.08 (0.11)	0.07 (1.4)	0.99 (2.48)	0.13 (1)
Aggravated Assault	0.79 (0.84)	0.63 (8.1)	4.74 (22.2)	1.38 (12.14)

Note. Statistics are generated from the 1990-2013 Uniform Crime Reports (UCR). Crimes rates are calculated as the number of crimes per 1,000 residents. Standard deviations are in parentheses. The number of observation is 17,784.

partment of Health and Human Services (2004), we calculate the social welfare spending of a state using Annual Survey of State Government Finances Datasets provided by U.S. Census Bureau (1990-2013a).[10] Table 2.2 shows summary statistics for minimum wages and social welfare spending in 2000. Panel (a) compares two groups of states where the first row shows the states with the minimum wage higher than the federal level, and the second row shows the others. This panel shows that 75 CZs in 10 states had the minimum wage higher than the federal minimum wage in 2000. These 10 states also spent more on social welfare than the other 10 states. Panel (b) shows the detailed minimum wages and the states' social welfare spending for the 10 states with higher minimum wages than the federal level. Many of them are located on the west coast. Interestingly, this panel shows variations exist in terms of minimum wage and social welfare spending within this group of states.

Table 2.2: Summary statistics of minimum wage and social welfare spending per capita in 2000

(a) Treated and control groups

States	Avg min wage	Avg SW spending	N of CZs	N of States
with min wage > Fed min	5.89	917.93	75	10
with min wage = Fed min	5.15	705.95	666	40
All states	5.30	748.34	741	50

(b) States with min wage > Fed min

State	Min wage	SW spending	N of CZs
Oregon	6.50	869.20	14
Washington	6.50	855.78	12
Connecticut	6.15	885.26	1
Massachusetts	6.00	982.07	5
California	5.75	544.61	18
Vermont	5.75	1148.04	3
Alaska	5.65	1278.05	15
Delaware	5.65	696.09	2
Rhode Island	5.65	1080.91	1
Hawaii	5.25	839.33	4

[10]Social welfare expenditure includes expenditures on cash assistance (E67, E68), Medicaid (E74), and non-health social services (E75, E77, F77, G77, E79, F79, G79). Following Department of Health and Human Services (2004), we exclude expenditures on public hospitals since the Census views spending on public hospitals as outside its social welfare category.

2.3 Identification Strategy

2.3.1 Difference-in-difference Model

To explore how China shock affected the US local communities' crime rates, we first revisit empirical findings by Pierce and Schott (2020) - that increased import competition from Chinese imports led to higher crime rates for all residents in local communities in the US. Then, we further study how this impact differs across demographic groups.

Denoting by $y_{c,t}$ the number of crimes per 1,000 individuals in CZ c and year t, we perform the baseline empirical exercises by estimating the following difference-in-difference (DD) model:

$$\begin{aligned} y_{c,t} \quad = \quad & \theta \cdot PostPNTR_t \times NTRGap_c + PostPNTR_t \times \boldsymbol{Z}_c' \gamma \\ & + \boldsymbol{Z}_{c,t}' \lambda + \delta_c + \delta_t + \varepsilon_{c,t}, \end{aligned} \tag{2.3}$$

where the first term on the right-hand side is the DD term of interest, an interaction of the CZ-level exposure to the China Shock and an indicator variable for the post-PNTR period; $PostPNTR_t = 1$ if $t \geq 2001$ and 0 otherwise. That is, a positive estimate for θ indicates the CZs that are located in highly impacted areas (first difference) result in an increase in crime rates after the imposition of PNTR (second difference).

The second term interacts with the post-PNTR dummy variable and CZ-level time-invariant control variables ($\boldsymbol{Z}_c$). The third term captures the impact of time-varying CZ characteristics ($\boldsymbol{Z}_{c,t}$). Lastly, δ_c and δ_t, represent CZ and year-fixed effects, capturing the potential impact of any time-invariant characteristics or aggregate shocks that could influence all CZs' activities within the same period (Dachis, Duranton, and Turner, 2012). Following Pierce and Schott (2020), $\boldsymbol{Z}_{c,t}$ in this chapter includes CZ's exposure to the overall US import tariff (NTR Rate) and the phasing out of the global Multi-Fiber Arrangement (MFA). $\boldsymbol{Z}_c$ includes all time-invariant controls used by Pierce and Schott (2020), such as

Chinese import tariff changes weighted by local employment, the 1990 share of population without a college degree, the 1990 share of military veterans, and the 1990 median household income. We further include more control variables in $\boldsymbol{Z}_c$ that may potentially affect crime rates, such as the 1990 share of residents younger than 25 years old, the 1990 share of whites, the 1990 share of blacks, and the 1990 share of males.[11] The estimation specifications are similar to the ones in Pierce and Schott (2020) but differs in the following aspects. First, Pierce and Schott look at crime rates by all residents while we look at them by demographic groups by age, gender, and race. Second, Pierce and Schott use county as a unit of observation whereas CZ is the unit of observation in this chapter, which are clusters of US counties characterized by strong within-cluster and weak between-cluster commuting ties. It provides a local labor market geography that covers the entire land area of the United States. Lastly, we include more variables $\boldsymbol{Z}_c$.

Specifically, since the magnitude of the coefficients cannot be interpreted directly from the estimates, we adopt the method from Pierce and Schott (2016) that calculated the implied impact of the coefficient estimates, which shows how the impact changes if we move a CZ from a heavily impacted area (75th percentile of the NTR Gap distribution) to a less-impacted area (25th percentile of the NTR Gap distribution). Recall that in the DD specification, θ is the coefficient of interest,

$$\begin{aligned} & \frac{\partial \left(E\left[y_{c,t}|PostPNTR=1\right]-E\left[y_{c,t}|PostPNTR=0\right]\right)}{\partial NTRGap_c} \\ = \quad & \theta. \end{aligned} \tag{2.4}$$

where θ captures the slope of $NTRGap$ on y change with respect to PostPNTR. Under a linearlity assumption between y changes and $NTRGap$, we can calculate the implied

[11] The time-invariant CZ-level attributes are obtained from the 1990 Decennial Census. These data can be downloaded from the Dexter Data Extractor from the University of Missouri, available at http://mcdc.missouri.edu.

impact as

$$impact = \hat{\theta} \left(NTRGap_{75th} - NTRGap_{25th} \right) \tag{2.5}$$

where $\hat{\theta}$ refers to the estimated coefficient for θ, and $NTRGap_{75th}$ refers to the 75th percentile of the NTRGap distribution. Equation 2.5 calculates the associated y-change if we move a CZ from 25th percentile to 75 percentile of the NTRGap distribution.

2.3.2 Difference-in-difference-in-difference Model

This chapter aims to examine if higher state-level minimum wage results in lower CZ-level crime rates in the China Shock's presence. Therefore, based on the DD specification, we added the third difference of minimum wage to the identification strategy. We estimate the following difference-in-difference-in-difference (DDD) regression model of the form:

$$\begin{aligned} y_{c,t} = {} & PostPNTR_t \times NTRGap_c \times (\mu_1 \cdot MW_c + \mu_2 \cdot SWE_c) \\ & + PostPNTR_t \times (\theta \cdot NTRGap_c + \beta \cdot MW_c + \beta_2 \cdot SWE_c + \boldsymbol{Z}_c' \gamma) \\ & + \boldsymbol{Z}_{c,t}' \lambda + \delta_c + \delta_t + \varepsilon_{c,t}, \end{aligned} \tag{2.6}$$

where MW_c refers to the log value of minimum wages and SWE_c refers to the log of state-level social welfare spending that a CZ c belongs to in the year 2000, one year prior to the shock. The coefficient of interest μ_1 measures the minimum wage's effect on local crime rates. A negative estimate for μ_1 indicates that a CZ located in a highly impacted area (first difference) with a higher level of minimum wage (third difference), would result in a lower crime rates after the imposition of PNTR (second difference). μ_2 controls for social welfare spending, which allows us to identify the impact of minimum wage that is free from confounding CZ-level characteristics.[12]

[12]Note the difference-in-difference and difference-in-difference-in-difference estimations used in this chapter only measure the immediate effect of crimes. They do not provide any information beyond the immediate point.

According to Equation 2.7, a higher minimum wage helps reduce crimes against negative income shock if μ_1 is negative.

$$\frac{\partial\left(E\left[y_{c,t}|PostPNTR=1\right]-E\left[y_{c,t}|PostPNTR=0\right]\right)}{\partial NTRGap_c}=\theta+\mu_1\times MW_c+\mu_2\times SWE_c \tag{2.7}$$

Likewise, to interpret the coefficient estimates from the DDD model, we calculate the implied impact for the minimum wages based on Equation 2.7. The implied impact of minimum wages can be derived by taking the slope of $NTRGap$ on y change with respect to $PostPNTR$, conditioning on MW_c :

$$\frac{\partial\left(E\left[y_{c,t}|PostPNTR=1,MW_c\right]-E\left[y_{c,t}|PostPNTR=0,MW_c\right]\right)}{\partial NTRGap_c}=\theta+\mu_1\times MW_c \tag{2.8}$$

Thus the implied impact can be defined as:

$$impact\left(MW_c\right)=\left(\hat{\theta}+\hat{\mu_1}\times MW_c\right)\left(NTRGap_{75th}-NTRGap_{25th}\right) \tag{2.9}$$

where the implied impact now depends on the value of minimum wage of a CZ c, MW_c. Therefore, we can now calculate and report the result obtained from the following equation:

$$\begin{aligned} & impact\left(MW_{75th}\right)-impact\left(MW_{25th}\right) \qquad (2.10)\\ = \;& \hat{\mu_1}\left(\left(MW_{75th}\right)-\left(MW_{25th}\right)\right)\left(NTRGap_{75th}-NTRGap_{25th}\right). \end{aligned}$$

In the case where there is not much variation in the state-level minimum wages, i.e., $MW_{75th}=MW_{25th}$, we can calculate

$$\hat{\mu_1}\left(\left(MW_{Fed}+1\right)-\left(MW_{Fed}\right)\right)\left(NTRGap_{75th}-NTRGap_{25th}\right) \tag{2.11}$$

which implies the change by raising minimum wage of $1 from the federal level.

2.4 Estimation Results

2.4.1 Baseline Results

Following Equation 2.3, we first estimate the China Shock's impact on property crimes. Table 2.3 reports the estimated DD coefficient θ from Equation 2.3 using the number of crimes per 1,000 residents as the dependent variable. The first column reports coefficient estimates for overall property crimes, which is a summation of the breakdown categories of crime reported in columns 2-5: burglary, larceny, motor vehicle theft, and arson.

As for economic significance, we report the implied impact of an interquartile shift in a CZ's exposure to PNTR on crime rates from Equation 2.5 and the social cost of crime.[13] We obtain the unit cost of index crimes in 2010 in the US from Chalfin (2015) and Heeks et al. (2018), and the statistics are reported in Table A.2. By multiplying the unit cost of crime with the corresponding implied impact, we can examine the magnitude of each crime's social costs due to the China Shock. While these are back-of-the-envelope estimates, the statistics provide references as to how much social costs these index crimes are associated with.

As indicated in Table 2.3 the DD point estimate of interest is positive and statistically significant for overall property crime and this significant pattern is mainly driven by larceny. To demonstrate the economic significance of the baseline DD results, we consider two CZs having different degrees of exposure to the China Shock: 0.057 for CZ A and 0.106 for CZ B. The former and the latter numbers, respectively, correspond to the first and third quartiles. When controlling for their different characteristics, CZ B exhibits a 0.374[14] lower increase in property crimes per 1,000 residents than CZ A, as indicated in the row of

[13]For each index crime, the cost employed is the median among estimates in the extant literature, including estimates on defensive expenditure, insurance administration, property stolen or damaged, lost output, health services, victim services, and police costs, etc.

[14]$0.374 = 7.594 \times (0.106 - 0.057)$.

implied impact. This change implies that the China Shock induced a $10,151 higher social cost from an 8.4 percent increase in property crime rates across CZs. Coefficient estimates for initial CZ attributes indicate that CZs with higher shares of the population aged 25 or more, higher percentages of people who did not attend college, and lower shares of veterans had larger increases in property crimes.

Table 2.4 reports estimates for the China Shock's impact on violent crimes. Compared to coefficient estimates from property crimes, these estimates are weaker in terms of significance and magnitude. The first column shows that the impact on overall violent crime is positive but insignificant. At the same time, murder and robbery, whose motives are often associated with financial concerns, significantly increased in CZs with higher exposure to the China Shock. The implied impact on overall violent crime is only about one-tenth of overall property crimes, 0.039. However, social costs induced by violent crimes are much more extensive than property crimes, since the cost of pain and suffering to violent crime victims is usually higher, likewise with associated health services and police costs (Chalfin, 2015). The results are consistent with Pierce and Schott (2020) in terms of statistical significance and magnitude.

There is a common conception that crime is linked to the economic climate - irregularities in the business cycle lead to higher crime rates. Ajimotokin, Haskins, and Wade (2015) argue that economic recessions lead to loss of jobs. High unemployment rate brings frustration to individuals due to a loss of disposable income and falling standard of living, which leads to people committing crimes. In this case, property crime significantly increased after the China Shock mainly due to financial crisis. Such findings are consistent with the criminal motivation theory, which suggests that economic stress increases criminal behavior (Landau, 1997; Hoover, 2000; Roberts and LaFree, 2001; Fergusson, Swain-Campbell, and Horwood, 2004; Weatherburn and Lind, 2006; Malby et al., 2012). According to these findings, illicit behaviors are caused by structurally induced frustrations at the gap between aspirations and expectations during an economic downturn.

Table 2.3: (Diff-Diff) PNTR and the property crime

	overall property	burglary	larceny	motor vehicle theft	arson
Post * NTR Gap	7.594**	0.541	6.654**	0.435	-0.037
	(3.585)	(0.512)	(3.259)	(0.404)	(0.055)
NTR rate	-14.517	-4.470	-10.946	1.106	-0.207
	(15.473)	(3.078)	(11.160)	(4.150)	(0.405)
MFA rate	-12.085	2.446	-15.804	1.689**	-0.415
	(17.648)	(1.802)	(16.977)	(0.798)	(0.278)
Post * Chinese tariff	0.444	0.557	0.223	-0.289	-0.048
	(2.903)	(0.932)	(2.011)	(0.388)	(0.062)
Post * Age 25+	5.548**	-0.190	5.855***	-0.123	0.007
	(2.493)	(0.531)	(1.859)	(0.356)	(0.062)
Post * White	2.049*	0.719**	1.273*	0.062	-0.004
	(1.048)	(0.311)	(0.705)	(0.139)	(0.029)
Post * Black	-0.154	0.118	-0.130	-0.163	0.021
	(1.157)	(0.315)	(0.803)	(0.136)	(0.036)
Post * Male	18.488**	2.831*	13.476**	1.897**	0.284
	(7.176)	(1.564)	(5.472)	(0.796)	(0.218)
Post * No College	6.067***	1.063***	4.289***	0.672***	0.043
	(1.194)	(0.281)	(0.899)	(0.144)	(0.031)
Post * Veteran	-16.633***	-3.035***	-12.413***	-1.099**	-0.087
	(4.250)	(0.922)	(3.278)	(0.451)	(0.134)
Post * Median HHI	0.472	0.225*	0.164	0.072	0.011
	(0.480)	(0.119)	(0.341)	(0.070)	(0.011)
Implied impact:	.374	.027	.328	.021	-.002
Impact/Average:	.084	.031	.1	.074	-.039
Social Cost	$10,151	$139	$650	$186	$-22
Observations	17,736	17,736	17,736	17,736	17,736
R^2	0.447	0.572	0.393	0.202	0.200

Note. i) Dependent variable is calculated as the number of crimes per 1,000 residents. ii) Error terms are clustered at CZ-level. iii) The number of observations is 17,736. iv) The number of CZs is 741. v) Implied/Average reports the ratio of the implied impact to the variable average.

Table 2.4: (Diff-Diff) PNTR and the violent crime

	overall violent	murder	rape	robbery	aggravated assault
Post * NTR Gap	0.786	0.052*	0.051	0.291*	0.391
	(1.049)	(0.029)	(0.059)	(0.154)	(0.939)
NTR rate	-6.032	-0.104	-1.464	-1.901**	-2.562
	(9.855)	(0.207)	(1.290)	(0.830)	(8.866)
MFA rate	0.740	-0.037	0.409	0.712	-0.343
	(2.666)	(0.138)	(0.275)	(0.489)	(2.349)
Post * Chinese tariff	-0.258	-0.008	-0.048	-0.243	0.042
	(1.449)	(0.068)	(0.110)	(0.218)	(1.430)
Post * Age 25+	-1.116	-0.008	0.100	-0.383**	-0.825
	(0.831)	(0.029)	(0.083)	(0.185)	(0.730)
Post * White	0.441	0.024**	-0.080	0.138***	0.360
	(0.643)	(0.011)	(0.088)	(0.049)	(0.639)
Post * Black	-1.729***	-0.063***	-0.203**	-0.208***	-1.256**
	(0.651)	(0.015)	(0.082)	(0.061)	(0.628)
Post * Male	6.534**	0.066	0.742***	1.284***	4.443
	(3.109)	(0.091)	(0.254)	(0.378)	(2.926)
Post * No College	0.856	-0.008	0.051	0.107*	0.706
	(0.522)	(0.014)	(0.034)	(0.059)	(0.480)
Post * Veteran	-1.609	-0.020	-0.424***	0.064	-1.229
	(1.701)	(0.045)	(0.146)	(0.367)	(1.486)
Post * Median HHI	-0.194	-0.013*	-0.010	-0.099**	-0.073
	(0.201)	(0.007)	(0.011)	(0.049)	(0.170)
Implied impact:	.039	.003	.003	.014	.019
Impact/Average:	.03	.078	.033	.091	.019
Social Cost	$218,139	$15,960	$449	$545	$1,611
Observations	17,736	17,736	17,736	17,736	17,736
R^2	0.513	0.353	0.331	0.712	0.461

Note. i) Dependent variable is calculated as the number of crimes per 1,000 residents. ii) Error terms are clustered at CZ-level. iii) The number of observations is 17,736. iv) The number of CZs is 741. v) Implied/Average reports the ratio of the implied impact to the variable average.

Given the DD estimation results, we further explore whether higher state-level minimum wages reduce overall CZ-level crime rates controlling for social welfare spending. Table 2.5 reports DDD regression estimates for property crime, confirming the mitigating role of minimum wages. Coefficient estimates in the first row show that higher minimum wages significantly reduced overall property crime and its four sub-categories. In terms of economic significance, the implied impact shows that an interquartile shift in the minimum wage distribution (from the first to the third quantiles) is associated with a decrease in overall property crime rates of 28.7 percent, and 33.3, 23.9, 67.7, and 43.7 percent for burglary, larceny, motor vehicle theft, and arson respectively. This corresponds to a reduction in social costs of $34,823, $1,475, $1,546, $1,748, and $234 respectively. The effect of social welfare spending on crime rates is reported in the second row in Table 2.5. The results show that more social welfare spending will increase property crimes, while it is only significant for burglary. The estimates from Table 2.5 confirm that minimum wage is the main driver for lower property crimes due to the China Shock.

Table 2.6 reports minimum wage's effect on violent crimes. Results show a weaker impact of minimum wage in reducing violent crimes. However, it still seems effective in reducing some types of violent crimes such as robbery and murder.[15] Financial motives may often cause this pattern. The results on minimum wage are consistent with previous papers that propose mechanisms to soften the China Shock's negative impact using similar DDD estimation strategies. Feenstra, Xu, and Ma (2019) show that the China Shock's effect on the housing market absorbs opposing forces from the labor market. Byun and Lee (2019) claim that a CZ with a better functioning local financial market experiences less increase in unemployment concerning the exposure to the China Shock. Economic reasoning suggests that higher minimum wage may reduce the possibility of being idle and lead youth to substitute from crime to legal work. Moreover, higher minimum wage may raise the opportunity cost of crime for those who remain employed (Hansen and Machin, 2001; Beauchamp and Chan, 2012; Beauchamp and Chan, 2014; Agan and Makowsky, 2018).

[15] Robbery: taking or attempting to take anything of value by force, threat of force, or by putting the victim in fear. Murder: unlawful killing of another human without justification or valid excuse.

Table 2.5: (Diff-Diff-Diff) Minimum wage and the property crime

	overall property	burglary	larceny	motor vehicle theft	arson
Post * NTR Gap * MinWage	-273.333**	-60.946***	-166.052*	-41.913***	-4.423**
	(120.704)	(20.394)	(97.271)	(10.652)	(1.852)
Post * NTR Gap * SWspending	13.413	2.895**	10.487	0.113	-0.083
	(9.004)	(1.417)	(7.975)	(0.856)	(0.164)
Post * NTR Gap	461.768**	101.742***	283.472*	69.351***	7.202**
	(199.544)	(33.445)	(161.493)	(17.448)	(3.028)
Post * SWspending	-0.071	-0.014	-0.154	0.079	0.018
	(0.713)	(0.123)	(0.613)	(0.070)	(0.014)
Post * MinWage	12.485	3.621**	6.355	2.305***	0.204
	(9.584)	(1.598)	(7.777)	(0.798)	(0.139)
NTR rate	-16.876	-4.708	-12.902	0.960	-0.226
	(15.279)	(2.993)	(11.101)	(4.157)	(0.393)
MFA rate	-14.219	1.902	-17.121	1.436*	-0.437
	(17.901)	(1.703)	(17.338)	(0.747)	(0.277)
Post * Chinese tariff	0.223	0.670	-0.089	-0.302	-0.055
	(2.742)	(0.900)	(1.939)	(0.342)	(0.071)
Post * Age 25+	6.053**	-0.116	6.267***	-0.109	0.010
	(2.475)	(0.520)	(1.866)	(0.360)	(0.062)
Post * White	1.533	0.670**	0.807	0.062	-0.006
	(1.076)	(0.300)	(0.774)	(0.130)	(0.026)
Post * Black	-0.716	0.055	-0.595	-0.192	0.015
	(1.128)	(0.305)	(0.803)	(0.124)	(0.034)
Post * Male	15.804**	2.105	12.090**	1.383*	0.227
	(6.797)	(1.461)	(5.230)	(0.765)	(0.217)
Post * No College	4.286***	0.765***	3.025***	0.480***	0.016
	(1.177)	(0.261)	(0.922)	(0.135)	(0.030)
Post * Veteran	-12.689***	-2.520***	-9.405***	-0.731*	-0.032
	(4.145)	(0.919)	(3.192)	(0.437)	(0.135)
Post * Median HHI	0.166	0.147	-0.019	0.032	0.005
	(0.442)	(0.105)	(0.325)	(0.065)	(0.010)
Implied impact (MinWage):	-1.283	-.286	-.78	-.197	-.021
Implied impact (SWspending):	.909	.196	.711	.008	-.006
Impact/Average (MinWage):	-.287	-.333	-.239	-.677	-.437
Impact/Average (SWspending):	.204	.228	.218	.026	-.118
Social Cost (MinWage):	$-34,823	$-1,475	$-1,546	$-1,748	$-234
Social Cost (SWspending):	$24,672	$1,011	$1,409	$71	$-67
Observations	17,736	17,736	17,736	17,736	17,736
R^2	0.450	0.576	0.395	0.205	0.201

Note. i) Dependent variable is calculated as the number of crimes per 1,000 residents. ii) Error terms are clustered at CZ-level. iii) The number of observations is 17,736. iv) The number of CZs is 741. v) Implied/Average reports the ratio of the implied impact to the variable average.

Table 2.6: (Diff-Diff-Diff) Minimum wage and the violent crime

	overall violent	murder	rape	robbery	aggravated assault
Post * NTR Gap * MinWage	-63.839	-1.573*	-0.371	-14.704***	-47.191
	(48.798)	(0.849)	(2.762)	(5.233)	(44.822)
Post * NTR Gap * SWspending	1.093	-0.009	-0.386*	0.309	1.179
	(3.501)	(0.085)	(0.211)	(0.424)	(3.236)
Post * NTR Gap	106.098	2.633*	0.525	24.559***	78.381
	(79.702)	(1.400)	(4.515)	(8.666)	(73.214)
Post * SWspending	0.137	0.014*	0.041*	0.012	0.070
	(0.310)	(0.007)	(0.023)	(0.041)	(0.286)
Post * MinWage	3.512	0.108*	-0.052	1.014**	2.443
	(3.650)	(0.062)	(0.213)	(0.406)	(3.342)
NTR rate	-6.228	-0.091	-1.450	-1.897**	-2.791
	(9.622)	(0.206)	(1.264)	(0.786)	(8.714)
MFA rate	0.263	-0.055	0.420	0.591	-0.693
	(2.653)	(0.137)	(0.277)	(0.476)	(2.368)
Post * Chinese tariff	-0.199	0.004	-0.054	-0.202	0.053
	(1.592)	(0.070)	(0.124)	(0.210)	(1.558)
Post * Age 25+	-1.047	-0.005	0.104	-0.381**	-0.765
	(0.834)	(0.028)	(0.087)	(0.190)	(0.733)
Post * White	0.404	0.024**	-0.081	0.147***	0.315
	(0.559)	(0.010)	(0.087)	(0.050)	(0.567)
Post * Black	-1.796***	-0.064***	-0.206**	-0.207***	-1.319**
	(0.609)	(0.014)	(0.082)	(0.059)	(0.593)
Post * Male	5.688**	0.028	0.708***	1.082***	3.870
	(2.869)	(0.089)	(0.237)	(0.376)	(2.690)
Post * No College	0.497	-0.021	0.030	0.060	0.429
	(0.455)	(0.013)	(0.030)	(0.052)	(0.419)
Post * Veteran	-0.990	-0.011	-0.393***	0.113	-0.699
	(1.722)	(0.046)	(0.148)	(0.356)	(1.511)
Post * Median HHI	-0.282	-0.018***	-0.015	-0.116**	-0.133
	(0.174)	(0.007)	(0.010)	(0.045)	(0.144)
Implied impact (MinWage):	-.3	-.007	-.002	-.069	-.222
Implied impact (SWspending):	.074	-.001	-.026	.021	.08
Impact/Average (MinWage):	-.235	-.226	-.023	-.439	-.22
Impact/Average (SWspending):	.058	-.018	-.342	.133	.079
Social Cost (MinWage):	$-1,677,995	$-37,240	$-299	$-2,684	$-18,823
Social Cost (SWspending):	$413,905	$-5,320	$-3,890	$817	$6,783
Observations	17,736	17,736	17,736	17,736	17,736
R^2	0.514	0.355	0.332	0.714	0.462

Note. i) Dependent variable is calculated as the number of crimes per 1,000 residents. ii) Error terms are clustered at CZ-level. iii) The number of observations is 17,736. iv) The number of CZs is 741. v) Implied/Average reports the ratio of the implied impact to the variable average.

2.4.2 Results on Age Groups

This section provides empirical evidence that the negative income shock disproportionately raised crime rates for young adults. The mitigating role of the minimum wage was also larger for them. The results suggest that a higher minimum wage may be useful in reducing young workers' criminal behavior who tend to be in the entry-level labor market and more likely to hold minimum wage jobs.

We run DD regression (Equation 2.3) with age groups of under 20, 20-29, 30-39, 40-49, and over 49. Table 2.7 reports results for overall property crime. The estimated DD coefficient with the 20-29 group is the largest and decreases as the age group gets older. The implied impact for the 20-29 age group is 1.816. It means a CZ on the 75th percentile of the NTR Gap distribution experienced 1.816 times higher increase in overall property crimes per 1,000 residents aged 20-29 years old than that on the 25th percentile. This change represents a 19 percent increase in property crimes across CZs. Estimates from Table 2.7 also show that the impact from the China Shock decreases as age increases, with those aged over 49 being the lowest - only 6 percent increase in property crimes due to the China Shock.

Table 2.8 reports the estimated DD coefficient θ for violent crimes. In comparison, violent crimes are less affected by the exposure to the China Shock than property crimes. Young adults aged 20-29 are still the most affected group, with the economic significance of a 6 percent increase in violent crimes after the China Shock. Results in Table 2.7 and Table 2.8 in combination suggest that negative income shock is more likely to drive young adults to commit crimes associated with the acquisition of property or economic gain.

This substantial impact on young adults is noteworthy. Pierce and Schott (2020) show the largest China Shock's impact on the middle-aged group in terms of mortality rates. However, the negative effects on the young-age group are not well documented. Greenland and Lopresti (2016) show that a CZ with higher exposure to the China Shock experienced a relative increase in high school graduation rate. A possible reason for this weaker impact on the young-age group could be their higher mobility across regions. Greenland, Lopresti, and McHenry (2019) show that population growth was slower in a CZ with higher exposure to the shock pronounced in young individuals. If entry-level workers' financial motives drive this more substantial impact on the young-age group, young adults should not have this considerable impact on violent crimes. Consistent with this conjecture, the strongest influence on young adults is not very clear for violent crimes where the 20-29 age group is

Table 2.7: (Diff-Diff) PNTR and the property crime by age group

	under 20	20-29	30-39	40-49	over 49
Post * NTR Gap	0.674	36.860***	18.421***	14.925**	0.796**
	(4.274)	(12.584)	(4.682)	(7.328)	(0.345)
NTR rate	3.324	-60.380	-25.431	-39.393***	-6.296**
	(35.353)	(40.671)	(18.940)	(14.509)	(3.137)
MFA rate	8.160	-73.465	-20.645	-31.187	-2.197
	(10.116)	(68.245)	(24.872)	(41.526)	(1.443)
Post * Chinese tariff	3.003	6.482	-0.541	1.330	0.209
	(5.691)	(7.472)	(3.914)	(2.199)	(0.554)
Post * Age 25+	9.969**	-3.619	-2.418	-0.975	1.300***
	(5.062)	(5.483)	(2.577)	(1.972)	(0.414)
Post * White	2.043	5.238***	3.398***	0.702	0.068
	(1.766)	(1.718)	(0.853)	(0.643)	(0.144)
Post * Black	3.239*	-4.276**	-6.189***	0.850	0.766***
	(1.807)	(2.087)	(1.169)	(0.680)	(0.180)
Post * Male	41.181***	33.511**	14.266**	-0.600	0.701
	(12.910)	(13.356)	(6.923)	(4.790)	(1.085)
Post * No College	12.337***	8.006***	4.279***	-0.092	0.151
	(2.132)	(2.770)	(1.286)	(1.188)	(0.173)
Post * Veteran	-38.004***	-15.383	-5.455	-2.376	-2.183***
	(7.611)	(10.716)	(5.034)	(4.847)	(0.625)
Post * Median HHI	1.626*	0.654	-0.802	-0.162	0.130**
	(0.846)	(1.028)	(0.492)	(0.425)	(0.062)
Implied impact:	.033	1.816	.907	.735	.039
Impact/Average:	.005	.19	.178	.263	.061
Observations	17,736	17,736	17,736	17,736	17,736
R^2	0.497	0.252	0.445	0.133	0.551

Note. i) Dependent variable is calculated as the number of crimes per 1,000 residents. ii) Error terms are clustered at CZ-level. iii) The number of observations is 17,736. iv) The number of CZs is 741. v) Implied/Average reports the ratio of the implied impact to the variable average.

still the most affected, with the 40-49 age group being second.

If the China Shock raised crime rates of young-age groups through monetary motivation, the minimum wage should be more effective in reducing crimes committed by young adults. To explore this effect, we run DDD regression (Equation 2.6) for each age group. As shown in Equation 2.7, a negative sign of μ_1 indicates a mitigating role of minimum wage on crimes, and its magnitude represents the size of mitigation. The results may not be solely driven by minimum wage itself but by a better social safety net of the local community. Therefore, in this section, we also include the social welfare spending in estimation.

Results for property crime are reported in Table 2.9. Coefficient estimates for the minimum wage are significant for age groups of under 20, 20-29, and 30-39, with the largest

Table 2.8: (Diff-Diff) PNTR and the violent crime rates by age group

	under 20	20-29	30-39	40-49	over 49
Post * NTR Gap	0.807	4.640*	1.470	3.708**	0.795**
	(0.697)	(2.644)	(1.660)	(1.734)	(0.322)
NTR rate	1.205	1.515	-3.788	6.273	-0.665
	(5.056)	(20.348)	(13.715)	(18.845)	(1.949)
MFA rate	-0.639	1.231	2.467	1.449	-0.592
	(2.024)	(7.969)	(4.941)	(3.104)	(0.731)
Post * Chinese tariff	-0.824	-1.889	-2.368	2.831	0.837
	(0.960)	(3.093)	(2.445)	(2.159)	(0.821)
Post * Age 25+	-0.222	-3.243	-2.452*	-0.905	0.038
	(0.814)	(2.373)	(1.445)	(1.097)	(0.184)
Post * White	0.383	0.692	0.835	-0.301	-0.146
	(0.266)	(0.858)	(0.684)	(0.363)	(0.095)
Post * Black	-1.162***	-4.800***	-2.925***	-1.913***	-0.404***
	(0.327)	(1.151)	(0.804)	(0.428)	(0.127)
Post * Male	7.933***	14.841**	6.202	2.536	0.227
	(2.182)	(6.660)	(4.863)	(2.972)	(0.838)
Post * No College	1.098***	0.376	0.539	0.258	-0.090
	(0.312)	(1.033)	(0.673)	(0.440)	(0.104)
Post * Veteran	-2.331	-3.176	-2.064	-0.594	-0.195
	(1.503)	(4.715)	(3.045)	(1.847)	(0.399)
Post * Median HHI	-0.199	-0.669	-0.559**	-0.038	-0.042
	(0.184)	(0.447)	(0.282)	(0.203)	(0.044)
Implied impact:	.04	.229	.072	.183	.039
Impact/Average:	.039	.065	.034	.155	.152
Observations	17,736	17,736	17,736	17,736	17,736
R^2	0.568	0.554	0.543	0.189	0.396

Note. i) Dependent variable is calculated as the number of crimes per 1,000 residents. ii) Error terms are clustered at CZ-level. iii) The number of observations is 17,736. iv) The number of CZs is 741. v) Implied/Average reports the ratio of the implied impact to the variable average.

magnitude on those who are under 20. The magnitude decreases as age increases. In terms of economic significance, the implied impact shows the change by raising the minimum wage of one dollar from the federal level will reduce overall property crime rates of 28.9 percent, and 21.6, 23.9, and 25.3 percent for the age group of under 20, 20-29, and 30-39 respectively, given an interquartile shift in exposure to PNTR. Social welfare spending does not present a significant pattern except for those aged 30-39, and all coefficient estimates on social welfare spending are positive. Table 2.10 reports estimates for violent crimes. Higher minimum wages statistically significantly mitigated violent crimes committed by those under 20, 40-49, and over 49.

Figure A.3 visualizes the estimated DDD coefficients with minimum wage μ_1 from Equation 2.6. The first column figures show estimated DDD coefficients for all property crimes and subcategories of property crimes of burglary, larceny, motor vehicle theft, and arson. The second column shows DDD coefficients for all violent crimes and its subcategories of violent category, including murder, rape, robbery, and aggravated assault.

For property crimes, figures in the first row present negative coefficients for all age groups, but the magnitudes decrease as the sample group gets older. We observe this pattern for all subcategories in property crimes except for arson, a crime that may not be committed out of financial reasons. In the second column of violent crimes, the signs of μ_1 are consistently negative but do not show a particularly more substantial impact on young adults.

Our estimates suggest that youth behavior is responsive to price incentives and that falling real wages may have been an essential determinant of rising youth crime during the 1970s and 1980s. Moreover, wage differentials explain a substantial component of both the racial differential in criminal participation and crime's age distribution. The mechanism of this phenomenon is studied in a series of research. Young adults' behavior is responsive to financial motives, and that increasing real wage may have been a vital determinant of falling youth crime (Grogger, 1998). While a minimum wage hike reduces crime's attractiveness as a source of income relative to legitimate work (Kallem, 2004), higher minimum wage may improve the legitimate labor market by enticing those who would commit crimes to enter the legitimate labor market (Loonam, 2020).

Table 2.9: (Diff-Diff-Diff) Minimum wage and the property crime by age group

	under 20	20-29	30-39	40-49	over 49
Post * NTR Gap * MinWage	-435.177**	-439.200*	-275.482***	-127.158	-20.397
	(210.678)	(246.596)	(99.384)	(93.233)	(18.155)
Post * NTR Gap * SWspending	8.051	45.434	21.378*	17.885	0.072
	(11.178)	(28.511)	(11.260)	(16.348)	(1.040)
Post * NTR Gap	719.042**	775.545*	478.995***	230.326	34.340
	(346.145)	(416.654)	(166.889)	(164.274)	(29.857)
Post * SWspending	0.726	-1.002	-0.143	-0.703	0.049
	(0.963)	(2.065)	(0.853)	(1.139)	(0.090)
Post * MinWage	16.552	16.959	14.983*	9.552	1.163
	(16.739)	(19.241)	(7.717)	(6.920)	(1.395)
NTR rate	-0.758	-66.013	-27.006	-39.850***	-6.342**
	(34.939)	(40.865)	(18.869)	(15.045)	(3.139)
MFA rate	5.656	-78.103	-23.649	-33.080	-2.332
	(9.445)	(69.870)	(25.184)	(42.593)	(1.426)
Post * Chinese tariff	1.793	6.400	0.200	2.200	0.221
	(5.443)	(7.197)	(3.782)	(2.247)	(0.539)
Post * Age 25+	10.683**	-2.015	-1.696	-0.669	1.310***
	(5.081)	(5.532)	(2.533)	(2.028)	(0.412)
Post * White	1.259	3.516*	2.791***	0.477	0.068
	(1.813)	(1.881)	(0.876)	(0.759)	(0.155)
Post * Black	2.266	-5.795***	-6.744***	0.707	0.753***
	(1.765)	(2.032)	(1.123)	(0.688)	(0.183)
Post * Male	36.820***	29.906**	10.960	-1.989	0.429
	(12.699)	(13.062)	(6.809)	(4.758)	(1.096)
Post * No College	9.192***	4.165	2.369*	-0.607	0.053
	(2.087)	(2.975)	(1.350)	(1.259)	(0.184)
Post * Veteran	-30.662***	-6.762	-2.102	-1.801	-2.016***
	(7.480)	(10.125)	(4.765)	(4.447)	(0.631)
Post * Median HHI	1.178	-0.012	-1.289***	-0.372	0.106*
	(0.796)	(1.018)	(0.483)	(0.424)	(0.063)
Implied impact (MinWage):	-2.043	-2.062	-1.293	-.597	-.096
Implied impact (SWspending):	.546	3.079	1.449	1.212	.005
Impact/Average (MinWage):	-.289	-.216	-.253	-.214	-.15
Impact/Average (SWspending):	.077	.322	.284	.434	.008
Observations	17,736	17,736	17,736	17,736	17,736
R^2	0.501	0.254	0.448	0.133	0.552

Note. i) Dependent variable is calculated as the number of crimes per 1,000 residents. ii) Error terms are clustered at CZ-level. iii) The number of observations is 17,736. iv) The number of CZs is 741. v) Implied/Average reports the ratio of the implied impact to the variable average.

Table 2.10: (Diff-Diff-Diff) Minimum wage and the violent crime by age group

	under 20	20-29	30-39	40-49	over 49
Post * NTR Gap * MinWage	-55.681**	-116.532	-55.161	-82.357***	-14.524*
	(22.087)	(77.566)	(50.785)	(29.246)	(8.195)
Post * NTR Gap * SWspending	0.596	3.929	2.352	0.031	1.383*
	(2.056)	(8.622)	(5.683)	(4.019)	(0.803)
Post * NTR Gap	92.539**	197.646	93.055	138.954***	25.139*
	(36.615)	(128.412)	(84.041)	(48.317)	(13.519)
Post * SWspending	0.243	0.275	0.200	-0.006	-0.126*
	(0.184)	(0.683)	(0.457)	(0.288)	(0.066)
Post * MinWage	3.191*	5.238	1.657	6.574***	1.274**
	(1.663)	(5.960)	(3.831)	(2.309)	(0.643)
NTR rate	1.208	0.798	-4.329	6.510	-0.709
	(4.893)	(19.949)	(13.454)	(18.805)	(1.927)
MFA rate	-1.118	0.280	2.000	0.894	-0.736
	(1.980)	(7.971)	(4.910)	(3.053)	(0.718)
Post * Chinese tariff	-0.665	-1.859	-2.422	3.058	0.886
	(1.029)	(3.191)	(2.645)	(2.126)	(0.804)
Post * Age 25+	-0.131	-2.974	-2.240	-1.037	0.017
	(0.815)	(2.384)	(1.449)	(1.127)	(0.185)
Post * White	0.345	0.460	0.629	-0.104	-0.123
	(0.256)	(0.833)	(0.665)	(0.368)	(0.089)
Post * Black	-1.222***	-5.054***	-3.127***	-1.791***	-0.385***
	(0.311)	(1.134)	(0.792)	(0.414)	(0.122)
Post * Male	7.021***	13.364**	5.513	1.439	0.132
	(2.131)	(6.440)	(4.737)	(2.938)	(0.819)
Post * No College	0.719**	-0.541	-0.074	0.256	-0.053
	(0.300)	(1.018)	(0.662)	(0.444)	(0.105)
Post * Veteran	-1.811	-1.420	-0.819	-0.837	-0.267
	(1.513)	(4.759)	(3.060)	(1.871)	(0.396)
Post * Median HHI	-0.313*	-0.867**	-0.678**	-0.083	-0.037
	(0.171)	(0.428)	(0.272)	(0.202)	(0.041)
Implied impact (MinWage):	-.261	-.547	-.259	-.387	-.068
Implied impact (SWspending):	.04	.266	.159	.002	.094
Impact/Average (MinWage):	-.256	-.157	-.121	-.328	-.264
Impact/Average (SWspending):	.04	.076	.074	.002	.363
Observations	17,736	17,736	17,736	17,736	17,736
R^2	0.571	0.555	0.544	0.190	0.397

Note. i) Dependent variable is calculated as the number of crimes per 1,000 residents. ii) Error terms are clustered at CZ-level. iii) The number of observations is 17,736. iv) The number of CZs is 741. v) Implied/Average reports the ratio of the implied impact to the variable average.

2.4.3 Results on Gender

We also examine the differential impacts of the China Shock on gender and race. Table 2.11 reports the DD regression results on gender. The China Shock witnesses a significantly positive increase in property crime, but no impact on violent crime. For property crime, both males and females are affected significantly, while the magnitude for males is larger. On average, the China Shock brings an 8.6 percent increase in property crimes across CZs for males and an 11.6 percent increase for females.

Table 2.11: (Diff-Diff) PNTR and the property crime by gender

	Property crimes		Violent crimes	
	male	female	male	female
Post * NTR Gap	11.369**	6.135***	2.288	0.554
	(5.101)	(2.346)	(1.591)	(0.358)
NTR rate	-24.441	-8.777	-0.863	0.712
	(20.638)	(11.886)	(12.363)	(3.093)
MFA rate	-18.965	-9.256	-0.356	-0.557
	(24.847)	(11.306)	(4.003)	(1.059)
Post * Chinese tariff	1.330	1.515	-1.036	0.284
	(4.493)	(1.807)	(2.038)	(0.628)
Post * Age 25+	11.109***	0.959	-1.675	-0.231
	(3.773)	(1.443)	(1.371)	(0.291)
Post * White	2.062	1.353***	0.786	-0.125
	(1.392)	(0.492)	(0.517)	(0.149)
Post * Black	-0.855	0.053	-3.258***	-0.595***
	(1.607)	(0.552)	(0.709)	(0.177)
Post * Male	37.589***	6.467*	10.148**	1.479
	(9.926)	(3.636)	(4.221)	(1.030)
Post * No College	7.680***	2.909***	0.772	0.223
	(1.687)	(0.671)	(0.629)	(0.143)
Post * Veteran	-27.081***	-5.959**	-3.068	-0.235
	(6.314)	(2.451)	(2.832)	(0.645)
Post * Median HHI	0.173	0.396	-0.577*	-0.077
	(0.673)	(0.253)	(0.300)	(0.061)
Implied impact:	.56	.302	.113	.027
Impact/Average:	.086	.116	.052	.067
Observations	17,736	17,736	17,736	17,736
R^2	0.471	0.411	0.599	0.540

Note. i) Dependent variable is calculated as the number of crimes per 1,000 residents. ii) Error terms are clustered at CZ-level. iii) The number of observations is 17,736. iv) The number of CZs is 741. v) Implied/Average reports the ratio of the implied impact to the variable average.

The China shock's impact on males has been well documented in research. The import competition from China, along with its accession into WTO, brought frustration to people who used to work in the manufacturing sectors due to a loss of disposable income (Kim, 2018; Pierce and Schott, 2016; Autor, Dorn, and Hanson, 2016; Caliendo, Dvorkin, and Parro, 2019b). The standard of living for most fell considerably, which put tremendous pressure on maintaining the accustomed lifestyle. This negative income shock is believed to have caused a significant increase in crime rates for males (Raphael and Winter-Ebmer, 2001; Lin, 2008; Mustard, 2010; Che, Xu, and Zhang, 2018).

Table 2.12: (Diff-Diff-Diff) Minimum wage and the violent crime by gender

	Property crimes		Violent crimes	
	male	female	male	female
Post * NTR Gap * MinWage	-388.151**	-133.360**	-80.683*	-33.879***
	(165.976)	(56.958)	(45.022)	(11.249)
Post * NTR Gap * SWspending	22.978*	6.552	1.938	1.538
	(12.398)	(5.992)	(5.011)	(1.191)
Post * NTR Gap	657.801**	227.742**	135.642*	56.749***
	(274.726)	(94.993)	(74.534)	(18.577)
Post * SWspending	-0.282	0.131	0.274	-0.094
	(0.976)	(0.442)	(0.406)	(0.097)
Post * MinWage	16.857	6.332	3.523	2.650***
	(13.209)	(4.458)	(3.367)	(0.880)
NTR rate	-28.256	-9.667	-1.310	0.704
	(20.169)	(11.851)	(12.072)	(3.001)
MFA rate	-22.138	-10.432	-0.994	-0.852
	(25.182)	(11.510)	(3.953)	(1.051)
Post * Chinese tariff	0.958	1.600	-1.018	0.394
	(4.242)	(1.722)	(2.234)	(0.625)
Post * Age 25+	11.956***	1.265	-1.483	-0.255
	(3.755)	(1.435)	(1.369)	(0.290)
Post * White	1.163	1.081**	0.627	-0.082
	(1.419)	(0.505)	(0.487)	(0.140)
Post * Black	-1.775	-0.230	-3.437***	-0.569***
	(1.537)	(0.531)	(0.683)	(0.172)
Post * Male	33.999***	4.892	9.059**	1.098
	(9.603)	(3.512)	(4.129)	(0.982)
Post * No College	4.978***	1.931***	0.101	0.204
	(1.701)	(0.679)	(0.609)	(0.138)
Post * Veteran	-20.965***	-4.063*	-1.814	-0.267
	(6.117)	(2.348)	(2.844)	(0.635)
Post * Median HHI	-0.273	0.185	-0.725**	-0.096*
	(0.630)	(0.241)	(0.285)	(0.056)
Implied impact (MinWage):	-1.822	-.626	-.379	-.159
Implied impact (SWspending):	1.557	.444	.131	.104
Impact/Average (MinWage):	-.281	-.241	-.175	-.393
Impact/Average (SWspending):	.24	.171	.061	.258
Observations	17,736	17,736	17,736	17,736
R^2	0.475	0.413	0.600	0.542

Note. i) Dependent variable is calculated as the number of crimes per 1,000 residents. ii) Error terms are clustered at CZ-level. iii) The number of observations is 17,736. iv) The number of CZs is 741. v) Implied/Average reports the ratio of the implied impact to the variable average.

When turning to the DDD regression results on gender, as reported in Table 2.12, we can see higher state-level minimum wages significantly mitigated the increasing pattern for both property and violent crimes. This mitigating effect is larger for males. The economic significance of the DDD coefficient estimates for minimum wages shows that a one-dollar increase in the (federal-level) minimum wage would decrease property crimes by 28.1 and 24.1 percent for males and females, and 17.5 and 39.3 percent of decrease in violent crimes for males and females respectively.[16]

Figure A.4 visualizes the estimated DDD coefficients with minimum wage on males and females. For property crimes, figures in the first row present similar patterns - there are negative coefficients for both genders, and the magnitude is larger for males. Patterns for violent crimes are a bit irregular - the negative coefficients are larger for males in murder, robbery, and aggravated assault.

2.4.4 Results on Race

Table 2.13 and Table 2.14 report results that show differential impacts of the China Shock on race. Except for blacks, we witness a significant increase for all races in terms of property crimes. The largest magnitude of the coefficient estimates falls on Asians. The economic significance shows that an interquartile shift in exposure to PNTR is associated with increases in property crime rates of 5, 40.5, and 30.8 percent among whites, Asians, and American Indians. Only black people experience a significant increase in violent crimes - an average of 36.6 percent increase across CZs.

Table 2.15 and Table 2.16 report DDD estimates for minimum wages and social welfare spending and Figure A.5 visualizes the coefficient estimates. Higher minimum wage significantly mitigated property crime increase for white and black people. A one-dollar increase in the federal-level minimum wage reduces property crime by 26 and 126 percent for whites and blacks, respectively. This economic significance is substantial. In contrast,

[16]See Equation 2.11. There is not much variation in the 2000 state-level minimum wage sample, with the 25th and the 75th distribution both \$5.15.

social welfare spending has no impact on racial groups, except for American Indians. However, we should interpret the coefficient estimates for American Indians with caution due to a small sample size. We do not see any significant patterns for violent crimes.

The differential impacts of the China Shock on racial groups may be relevant to racial unemployment rates. According to Massourakis, Rezvani, and Yamada (1984) and Smith, Devine, and Sheley (1992), black unemployment seems to exert a more substantial influence on crimes than white unemployment. Prolonged structural unemployment that hit blue-collar workers may weaken the legitimacy of legal earning activities and consequently push these people towards crime.

Table 2.13: (Diff-Diff) PNTR and the property crime by race

	white	black	asian	american indian
Post * NTR Gap	6.116**	35.758	51.333**	40.941**
	(2.712)	(45.361)	(24.102)	(17.242)
NTR rate	-20.182	-315.623*	-96.704	113.564
	(12.579)	(175.226)	(93.622)	(104.410)
MFA rate	-7.647	13.220	-52.127*	13.188
	(12.708)	(122.842)	(28.516)	(24.527)
Post * Chinese tariff	0.752	77.115	-30.352	-4.333
	(3.037)	(74.081)	(18.526)	(21.539)
Post * Age 25+	6.683***	23.597	-41.827	-36.189
	(2.165)	(107.171)	(32.070)	(27.996)
Post * White	1.736**	0.052	-6.595	-13.357***
	(0.757)	(20.311)	(5.445)	(2.861)
Post * Black	2.976***	34.186*	-0.569	-8.846**
	(0.871)	(17.577)	(6.701)	(3.444)
Post * Male	12.213**	-62.873	-145.939	-69.174
	(5.934)	(126.730)	(98.781)	(61.081)
Post * No College	4.586***	12.215	8.697	8.331*
	(0.955)	(19.310)	(7.275)	(4.807)
Post * Veteran	-14.039***	-44.016	0.063	91.000**
	(3.809)	(102.179)	(51.104)	(41.480)
Post * Median HHI	0.476	16.285	13.058***	4.781**
	(0.356)	(10.348)	(3.518)	(1.859)
Implied impact:	.301	1.761	2.529	2.017
Impact/Average:	.05	.366	.405	.308
Observations	17,736	17,379	17,557	17,676
R^2	0.537	0.179	0.078	0.208

Note. i) Dependent variable is calculated as the number of crimes per 1,000 residents. ii) Error terms are clustered at CZ-level. iii) The number of observations is 17,736. iv) The number of CZs is 741. v) Implied/Average reports the ratio of the implied impact to the variable average.

Table 2.14: (Diff-Diff) PNTR and the violent crime by race

	white	black	asian	american indian
Post * NTR Gap	0.964	47.729**	6.477	10.212
	(0.743)	(22.868)	(4.301)	(6.561)
NTR rate	0.702	-125.581*	-6.618	45.072*
	(7.383)	(72.761)	(21.903)	(25.433)
MFA rate	-0.065	-38.018	-15.003	-6.151
	(1.776)	(30.478)	(9.509)	(14.286)
Post * Chinese tariff	-0.794	117.676	-1.242	6.011
	(0.889)	(90.810)	(5.255)	(8.335)
Post * Age 25+	0.092	-24.055	-4.672	-17.012
	(0.613)	(19.618)	(8.040)	(13.091)
Post * White	0.281	0.623	-0.596	-1.915
	(0.242)	(4.613)	(1.184)	(1.419)
Post * Black	-0.405	-1.803	-0.011	-0.523
	(0.277)	(5.610)	(1.397)	(1.284)
Post * Male	3.596*	-110.325	-6.293	6.208
	(2.136)	(69.274)	(13.882)	(18.825)
Post * No College	0.266	2.548	0.735	4.001**
	(0.289)	(5.047)	(1.115)	(1.930)
Post * Veteran	-1.395	38.035	11.598	28.861**
	(1.417)	(25.788)	(11.277)	(12.824)
Post * Median HHI	-0.109	-1.660	1.197	1.834
	(0.120)	(2.164)	(1.197)	(1.758)
Implied impact:	.047	2.351	.319	.503
Impact/Average:	.05	.366	.405	.308
Observations	17,736	17,379	17,557	17,676
R^2	0.564	0.101	0.079	0.083

Note. i) Dependent variable is calculated as the number of crimes per 1,000 residents. ii) Error terms are clustered at CZ-level. iii) The number of observations is 17,736. iv) The number of CZs is 741. v) Implied/Average reports the ratio of the implied impact to the variable average.

Table 2.15: (Diff-Diff-Diff) Minimum wage and the property crime by race

	white	black	asian	american indian
Post * NTR Gap * MinWage	-210.591**	-4713.445*	1261.466	-240.335
	(102.669)	(2812.840)	(1571.145)	(360.665)
Post * NTR Gap * SWspending	9.975	105.997	-47.462	88.534*
	(7.041)	(98.411)	(60.229)	(45.955)
Post * NTR Gap	355.975**	7816.774*	-2038.903	466.928
	(169.577)	(4628.862)	(2589.671)	(612.135)
Post * SWspending	-0.031	-8.982	1.231	-10.567**
	(0.561)	(8.792)	(5.733)	(4.468)
Post * MinWage	7.785	326.230*	-74.327	25.378
	(8.210)	(184.155)	(124.364)	(27.698)
NTR rate	-22.603*	-329.087*	-89.541	106.103
	(12.351)	(173.165)	(94.404)	(101.919)
MFA rate	-9.111	-16.073	-42.193	10.447
	(12.852)	(120.684)	(28.304)	(24.536)
Post * Chinese tariff	0.211	83.122	-30.618	-5.343
	(2.711)	(74.688)	(19.013)	(22.093)
Post * Age 25+	7.142***	18.990	-42.449	-37.254
	(2.158)	(106.966)	(32.512)	(27.774)
Post * White	1.208	5.844	-6.115	-13.100***
	(0.796)	(20.595)	(6.701)	(2.999)
Post * Black	2.414***	36.777**	0.476	-8.386**
	(0.841)	(17.765)	(7.403)	(3.558)
Post * Male	10.412*	-114.054	-131.735	-62.970
	(5.756)	(133.356)	(100.954)	(60.503)
Post * No College	3.007***	7.215	13.613*	12.639**
	(0.978)	(22.452)	(8.161)	(4.927)
Post * Veteran	-10.219***	-28.293	-9.971	87.733**
	(3.692)	(97.413)	(52.009)	(41.620)
Post * Median HHI	0.264	15.006	14.065***	6.352***
	(0.340)	(10.433)	(3.807)	(2.158)
Implied impact (MinWage):	-.989	-22.129	5.922	-1.128
Implied impact (SWspending):	.676	7.184	-3.217	6
Impact/Average (MinWage):	-.26	-1.26	1.603	-.197
Impact/Average (SWspending):	.177	.409	-.87	1.049
Observations	17,736	17,379	17,557	17,676
R^2	0.541	0.180	0.078	0.209

Note. i) Dependent variable is calculated as the number of crimes per 1,000 residents. ii) Error terms are clustered at CZ-level. iii) The number of observations is 17,736. iv) The number of CZs is 741. v) Implied/Average reports the ratio of the implied impact to the variable average.

Table 2.16: (Diff-Diff-Diff) Minimum wage and the violent crime by race

	white	black	asian	american indian
Post * NTR Gap * MinWage	-26.964	-486.532	41.028	29.490
	(22.282)	(305.013)	(88.952)	(97.480)
Post * NTR Gap * SWspending	1.042	45.320	-11.332	-20.438
	(2.685)	(37.285)	(7.594)	(20.882)
Post * NTR Gap	45.677	862.666*	-65.077	-45.887
	(36.930)	(516.351)	(147.641)	(163.252)
Post * SWspending	-0.004	-6.437	0.990	0.539
	(0.208)	(4.026)	(0.686)	(2.295)
Post * MinWage	0.846	45.368*	-1.283	-0.674
	(1.681)	(26.290)	(6.923)	(8.226)
NTR rate	0.339	-128.422*	-5.020	46.278*
	(7.330)	(74.130)	(21.900)	(26.335)
MFA rate	-0.219	-41.141	-14.559	-4.606
	(1.751)	(31.096)	(9.598)	(14.161)
Post * Chinese tariff	-0.909	118.773	-0.866	5.305
	(0.929)	(90.277)	(5.273)	(8.116)
Post * Age 25+	0.147	-26.251	-4.755	-17.692
	(0.618)	(20.107)	(8.075)	(13.211)
Post * White	0.210	2.152	-0.349	-1.237
	(0.237)	(4.860)	(1.208)	(1.380)
Post * Black	-0.483*	-0.579	0.186	-0.061
	(0.273)	(5.440)	(1.430)	(1.294)
Post * Male	3.398	-112.629	-6.813	6.573
	(2.092)	(68.958)	(14.428)	(17.968)
Post * No College	0.060	6.007	0.804	4.934*
	(0.287)	(6.002)	(1.248)	(2.676)
Post * Veteran	-0.855	34.933	10.610	27.277**
	(1.432)	(25.681)	(11.332)	(12.506)
Post * Median HHI	-0.129	-0.704	1.097	2.094
	(0.115)	(2.211)	(1.183)	(1.982)
Implied impact (MinWage):	-.127	-2.284	.193	.138
Implied impact (SWspending):	.071	3.072	-.768	-1.385
Impact/Average (MinWage):	-.132	-.356	.244	.085
Impact/Average (SWspending):	.074	.478	-.974	-.849
Observations	17,736	17,379	17,557	17,676
R^2	0.564	0.101	0.079	0.083

Note. i) Dependent variable is calculated as the number of crimes per 1,000 residents. ii) Error terms are clustered at CZ-level. iii) The number of observations is 17,736. iv) The number of CZs is 741. v) Implied/Average reports the ratio of the implied impact to the variable average.

2.5 Robustness

In this section, we examine the robustness of the DD and DDD results from two dimensions. First we include a full set of year dummies in Equation 2.3 to account for the potential serial correlation problem. Second we control for the opioid supply that may lead to surging crime rate.

Since DD specification is usually subject to serial correlation in the error terms when using data spanning several years, especially when including both a level and trend effect in the same estimation when using time series data (Bertrand, Duflo, and Mullainathan, 2004; Galster, Tatian, and Pettit, 2004). Following Pierce and Schott (2016), we replace the $PostPNTR_t$ indicator used in Equation 2.3 with interactions of the $NTRGap_c$ and the full set of year dummies to determine whether there is a relationship between the NTR gap and crime rates in the years before 2001.

$$\begin{aligned} y_{c,t} = & \sum_t \theta_t \cdot \mathbf{1}\{year = t\} \times NTRGap_c + \sum_t \gamma_t \cdot \mathbf{1}\{year = t\} \times \boldsymbol{Z'_c} \\ & + \boldsymbol{Z'_{c,t}}\lambda + \delta_c + \delta_t + \varepsilon_{c,t} \end{aligned} \quad (2.12)$$

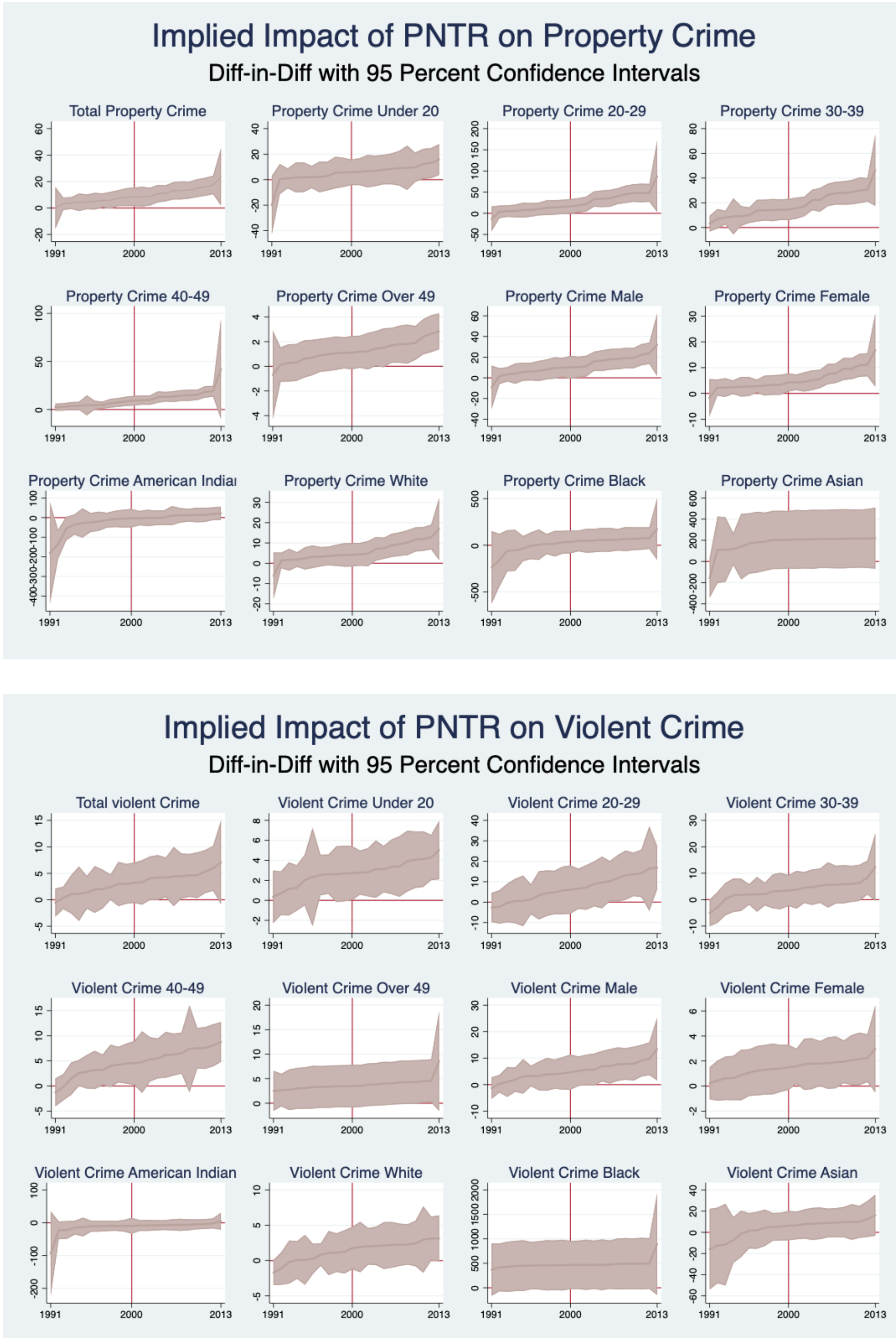
Likewise for the DDD model, we estimate a version of Equation 2.6 with interactions of an indicator variable for each year of 1990-2013,

$$\begin{aligned} y_{c,t} = & NTRGap_c \times (\sum_t \mu_{1t} \cdot \mathbf{1}\{year = t\} \times MW_c + \sum_t \mu_{2t} \cdot \mathbf{1}\{year = t\} \times SWE_c) \\ & + \sum_t \theta_t \cdot \mathbf{1}\{year = t\} \times NTRGap_c + \sum_t \beta_t \cdot \mathbf{1}\{year = t\} \times MW_c \\ & + \sum_t \beta_{2t} \cdot \mathbf{1}\{year = t\} \times SWE_c + \sum_t \gamma_t \cdot \mathbf{1}\{year = t\} \times \boldsymbol{Z'_c} + \\ & + \boldsymbol{Z'_{c,t}}\lambda + \delta_c + \delta_t + \varepsilon_{c,t} \end{aligned} \quad (2.13)$$

Surging opioid abuse may also be a contributing factor to the crime rate increases. The United States has experienced an unprecedented crisis related to the misuse and addiction to opioids. The crisis, which is often referred to as the opioid epidemic, started in the 1990s and continued through 2010 with a massive increase in prescribed opioids associated with lax prescribing regulations and aggressive marketing efforts in the pharmaceutical industry. Hammersley et al. (1989) and Dave, Deza, and Horn (2018) found that the concurrent opioid epidemic may bring an accompanying rise in crime. Opioid-related criminal offenses include crimes directly related to supporting one's addiction, such as stealing to pay for drugs. Moreover, many people abusing opioids lead a lifestyle that prompts them to associate with others engaged in illicit activity, including violent crimes, trafficking, and prostitution. Therefore, exogenous increases in opioid supply in areas more exposed to PNTR could lead to a spurious increase in the crime rate. Following Pierce and Schott (2020), we include in Equation 2.12 and Equation 2.13 the interaction of opioid regulation in $\boldsymbol{Z}_c'$ with the full set of year dummies in $\sum_t \gamma_t \mathbf{1}\{year = t\}$ as a robustness check. These opioid regulation data track a variety of types of legislation covering categories such as prescription monitoring databases, prevention of "doctor-shopping" for prescriptions and regulation of pain clinics.[17]

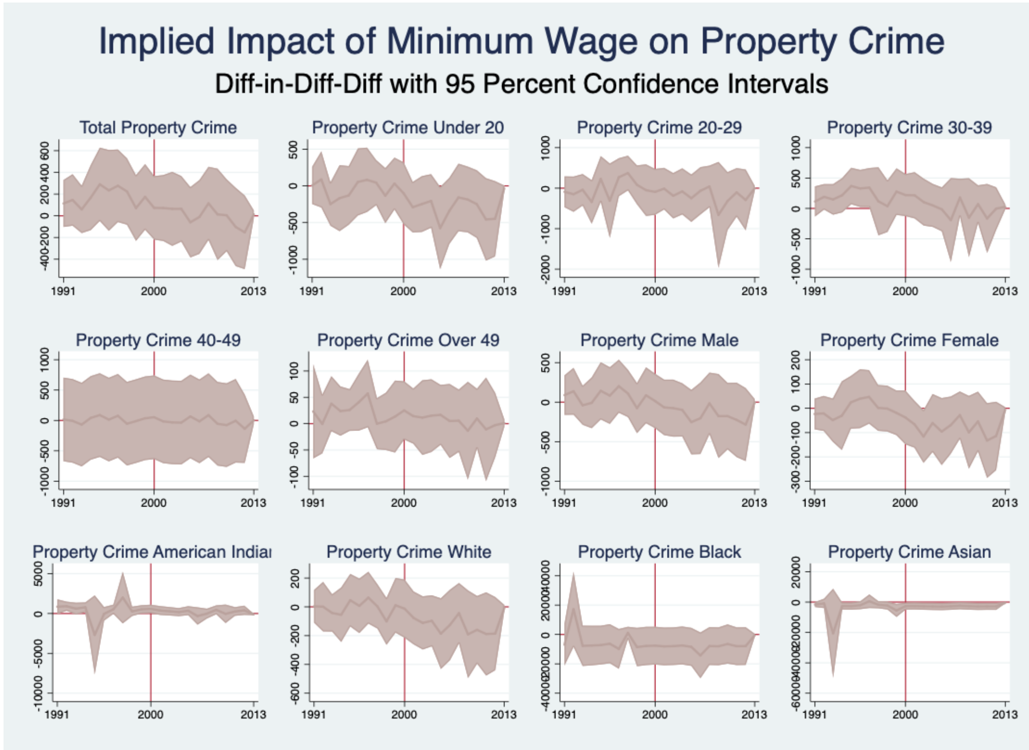
Figure 2.2 presents a matrix of graphs for reviewing the results of these estimations visually from Equation 2.12. Each panel of the figure uses the estimated DD parameters of interest θ_t from a separate regression on overall property crime, overall violent crime, and the breakdown of socio-economic groups of age, gender and race. The graphs also display the 95 percent confidence interval associated with an interquartile shift in CZ's NTR gaps.

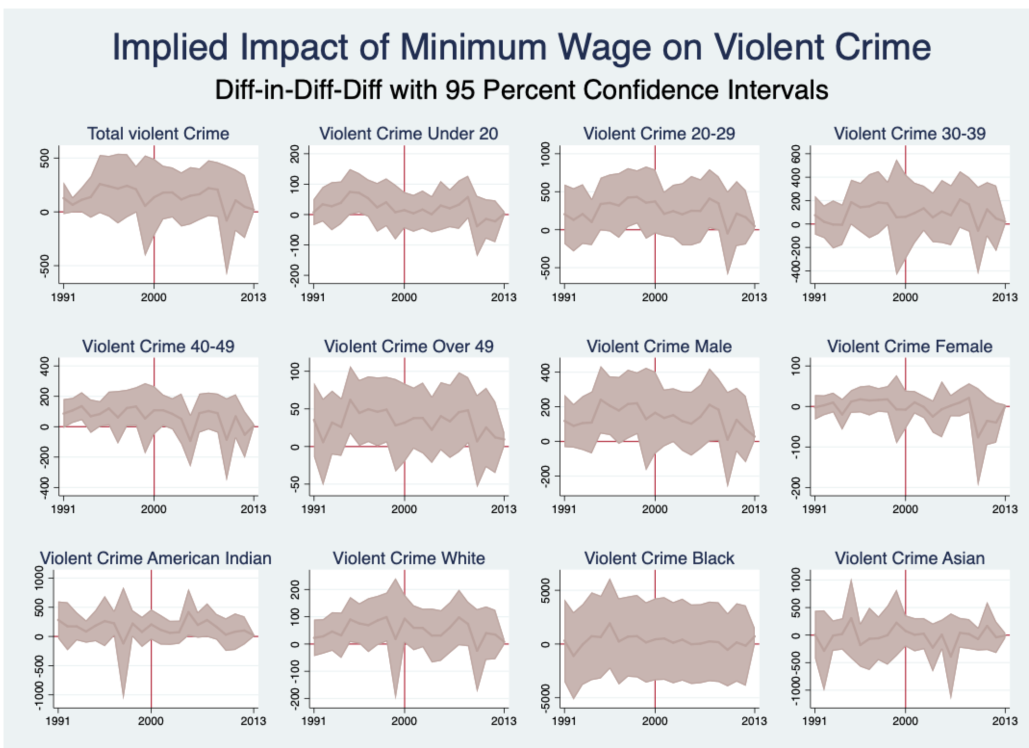
[17]We use data collected and summarized by Meara et al. (2016) and Pierce and Schott (2020) on state-level legislation pertaining to opioid regulation. For each state, opioid legislation is the sum of all legislation categories enacted over the years from 2006 to 2012.



Note. Figures display the 95 percent confidence interval of the implied impact of an interquartile shift in a CZ's exposure to PNTR on crime rates using estimates from Equation (Equation 2.12) for overall property crime, overall violent crime, and the breakdown of socio-economic groups of age, gender and race.

Figure 2.2: Implied impact of PNTR





Note. Figures display the 95 percent confidence interval of the implied impact of minimum wages using estimates from (Equation 2.13) for overall property crime, overall violent crime, and the breakdown of socio-economic groups of age, gender and race.

Figure 2.3: Implied impact of minimum wage

As indicated in the upper panel of Figure 2.2, we find that the confidence intervals for overall property crime, different gender and age groups, and whites are statistically indistinguishable from zero before 2000, but take a spike around the time of the change in policy in 2000, and remain elevated through 2013. This pattern is robust to the baseline results reported in Table 2.3. Consistent with Table 2.4, the lower panel of violent crimes do not show significant patterns. Figure 2.3 reports similar DDD estimation patterns for the minimum wage from Equation 2.13. The graphs confirm the robustness of the DDD regression results that higher minimum wage may play a mitigating role in property crime increase.

2.6 Potential Mechanisms

The previous sections show that CZs with higher trade liberalization exposure experienced a significant increase in overall property crime. A higher minimum wage may have a mitigating effect on increasing crime rates. One potential mechanism is via labor market disruptions through which higher minimum wage might result in a lower crime rate. People without work or with intermittent employment are more likely to engage in criminal or socially unacceptable behavior, which may be due to financial struggles with unemployment (Crutchfield, 2011), and this effect is found to be stronger for young adults (Allan and Steffensmeier, 1989).

Another potential mechanism is via increased disability take-up. Permanent job destruction has a significant effect on disability program participation. The rise in expenditures on Disability Insurance (DI) and Supplemental Security Income (SSI) coincided with a sharp reduction in the labor-force participation and relative earnings of the low-skilled men (D. Black and Sanders, 2002). Here it may constitute an additional channel by which worse economic times are associated with higher opioid use. If workers who were displaced by trade liberalization applied for disability, they might have been introduced to prescription opioid painkillers as part of the process. Therefore, the opioid-driven crime rates would increase after the US trade policy change as argued in the robustness section.

In this section, following Pierce and Schott (2020), we employ the unemployment rate as the measure of job availability and two types of disability measures - real disability payments and the number of disabled workers - to examine potential mechanisms through the labor market.[18] We estimate Equation 2.3 and Equation 2.6 with these three variables as dependent variables. Table 2.17 and Table 2.18 report the results.

Table 2.17: Mechanism: (Diff-Diff) Minimum wage and labor market outcomes

	Unemployment Rate	Disability Transfers	Disabled Workers
Post * NTR Gap	15.860***	1.603***	0.630***
	(1.531)	(0.363)	(0.108)
NTR rate	6.892	-1.027	0.226
	(12.076)	(2.323)	(0.891)
MFA rate	-40.804***	1.896**	-0.134
	(5.686)	(0.886)	(0.207)
Post * Chinese tariff	0.561	-0.528	-0.032
	(2.445)	(0.617)	(0.128)
Post * Age 25+	8.337***	0.081	-0.673***
	(1.847)	(0.338)	(0.132)
Post * White	1.844	-0.574***	-0.054
	(1.121)	(0.130)	(0.051)
Post * Black	3.853***	-0.136	-0.137**
	(1.260)	(0.148)	(0.060)
Post * Male	3.348	0.131	-0.834**
	(5.237)	(1.045)	(0.377)
Post * No College	-3.550***	-1.160***	-0.104**
	(0.854)	(0.157)	(0.053)
Post * Veteran	-4.848	0.046	0.917***
	(2.963)	(0.738)	(0.190)
Post * Median HHI	1.232***	-0.117**	0.035*
	(0.329)	(0.056)	(0.020)
Implied impact:	.781	.079	.031
Impact/Average:	.127	.009	.004
Observations	17,736	17,577	10,346
R^2	0.821	0.989	0.999

Note. i) Disability transfers and disabled workers are log disability transfer payments and log number of disabled workers. ii) Error terms are clustered at CZ-level. iii) The number of CZs is 741. iv) Implied/Average reports the ratio of the implied impact to the variable average.

[18] Data used in this section are based on Pierce and Schott (2020)'s calculations. The unemployment rates are obtained from the US Bureau of Labor Statistics, available at https://download.bls.gov/pub/time.series/la/. Disability transfers data come from the US Bureau of Economic Analysis and data on disabled workers are obtained from Social Security Administration.

Table 2.18: Mechanism: (Diff-Diff-Diff) Minimum wage and labor market outcomes

	Unemployment Rate	Disability Transfers	Disabled Workers
Post * NTR Gap * MinWage	-98.394***	-8.885**	2.734
	(22.288)	(3.629)	(2.277)
Post * NTR Gap * SWspending	-0.949	0.270	0.430**
	(2.005)	(0.325)	(0.205)
Post * NTR Gap	177.224***	16.271***	-3.705
	(36.782)	(5.987)	(3.757)
Post * SWspending	0.125	-0.097***	-0.044**
	(0.168)	(0.027)	(0.017)
Post * MinWage	4.348***	1.390***	-0.172
	(1.666)	(0.271)	(0.170)
NTR rate	6.113	-0.928	0.225
	(4.747)	(0.777)	(0.409)
MFA rate	-41.156***	1.801***	-0.132
	(3.990)	(0.645)	(0.241)
Post * Chinese tariff	0.181	-0.312*	-0.039
	(0.894)	(0.179)	(0.091)
Post * Age 25+	8.336***	-0.009	-0.670***
	(0.629)	(0.104)	(0.064)
Post * White	1.821***	-0.483***	-0.062***
	(0.210)	(0.036)	(0.021)
Post * Black	3.745***	-0.065	-0.140***
	(0.252)	(0.042)	(0.026)
Post * Male	2.438	-0.055	-0.761***
	(1.833)	(0.304)	(0.187)
Post * No College	-4.004***	-1.012***	-0.087***
	(0.301)	(0.049)	(0.031)
Post * Veteran	-3.623***	-0.291*	0.910***
	(1.016)	(0.165)	(0.104)
Post * Median HHI	1.198***	-0.103***	0.042***
	(0.112)	(0.018)	(0.011)
Implied impact (MinWage):	-.462	-.042	.013
Implied impact (SWspending):	-.064	.018	.029
Impact/Average (MinWage):	-.075	-.005	.002
Impact/Average (SWspending):	-.01	.002	.004
Observations	17736	17577	10346
R^2	0.822	0.989	0.999

Note. i) Disability transfers and disabled workers are log disability transfer payments and log number of disabled workers. ii) Error terms are clustered at CZ-level. iii) The number of CZs is 741. iv) Implied/Average reports the ratio of the implied impact to the variable average.

Table 2.17 and Table 2.18 confirm the hypothesis that PNTR might lead to an increased unemployment rate, which ultimately leads to an increase in crime rates. The economic significance shows that an interquartile shift in exposure to PNTR is associated with increases in the unemployment rate of 12.7 percent. Furthermore, a higher minimum wage significantly reduced the unemployment rate, with an economic significance of 7.5 percent. These results support the literature that poor labor market conditions create a stressful state that renders individuals susceptible to criminal behavior to overcome their economic problems or make illegitimate pursuits of an attractive alternative to poorly paid work (Allan and Steffensmeier, 1989).

Results on disability transfers and the number of disabled workers witness a significant increase after the China Shock. A higher minimum wage reduced real disability payments.[19] These results substantiate findings in previous literature that the China Shock brought the US labor market disruptions, leading many laid-off workers to apply for disability payments and misuse opioid products. Therefore, the crime rate increased. With a higher level of minimum wages, many vulnerable workers were drawn back to the legitimate labor market, reducing their reliance on DI and SSI programs, as well as potential substance abuse, which ultimately leads to crime rate reduction.

2.7 Conclusion

This chapter examines the role of minimum wages on local crime rates in the US upon China's accession into WTO in 2001. We find that CZs with higher trade liberalization exposure experienced a significant increase in overall property crime, and the results are significant across gender, age, and racial groups. However, results also show that the minimum wage may have a buffering effect on crimes. For CZs with higher state-level minimum wages before the China Shock, they experienced a reduction in overall property crime, and this effect is more substantial for young adults and white people. Meanwhile, we do not

[19] The insignificance result on disability workers for DDD regression might be due to that data is only available at CZ level after 2000.

find a significant impact of social welfare spending. We also find the potential mechanism is via labor market disruptions through which a higher minimum wage results in a lower crime rate. Results indicate the China Shock brought significant increase in unemployment rate and disability transfers, while higher minimum wages reduced these two dimensions. The estimation results are robust to including a full set of year dummies to address the serial correlation problem and controlling the opioid supply that may lead to a surging crime rate.

Our results suggest that minimum wage played a significant role in reducing crime rates due to the China Shock. One interpretation of that is that a higher minimum wage reduces crime in the presence of a negative income shock as it functions as a form of insurance. What this chapter does not answer is whether increasing the minimum wage when a negative income shock occurs (or as a result of it) would result in the same effect. It is possible that in such a circumstance we would not observe a reduction in crime rates. It may be the case that a higher minimum wage must be in place so that the labor market is in an equilibrium before the negative income shock hits.

This chapter delivers a more nuanced perspective to literature that studies the link between minimum wage and crime in the presence of a negative income shock. Understanding the relationship between criminal activity and prime variables such as minimum wage will allow us to plan the most effective way to make our country, as a whole, a safer place to live. The ability to lower crime rates nationwide will bring about many benefits such as increased domestic and foreign investment, better overall quality of education and housing, and a reduction in inequality.

CHAPTER 3

MULTIDIMENSIONAL IMPACTS OF TRADE LIBERALIZATION ON YOUNG ADULTS

3.1 Introduction

The US-China trade liberalization in 2001 created a considerable economic upheaval in the manufacturing sector in the United States. Long-term effects may include deteriorated labor conditions, rise in transfer payments for unemployment, disability, retirement, and healthcare in more trade-exposed labor markets, and intra-household adjustments in work dynamics.

There is a growing literature about the impacts of increased import competition from China on the workers' labor conditions. The seminal work of Pierce and Schott (2020) focused on the decline of US manufacturing employment in the 2000s, which showed that a county with higher exposure to trade liberalization with China tends to have higher mortality due to stress-related causes. The higher mortality is concentrated among middle-aged white males. Autor, Dorn, and Hanson (2013) found that a regional economy with higher exposure to the trade shock tends to show a higher unemployment rate and lower average wage. In a similar study, Stuart (2021) examined the long-run effects of the 1980-1982 recession on education and income. The author found that the economic recession is associated with decreased earnings per capita and four-year college degree attainment reduction.

The deteriorated labor market outcomes may directly impact workers in the trade-exposed sectors, however, what is often ignored, is that this effect may also incur high social costs that can extend beyond individuals and families and spill over into the more extensive social settings where they have connection. This spillover effect is considerable especially when it is delivered from the older generation to the younger generation. Previous research supports the argument that job quality may be a crucial mechanism underlying the intergenerational transmission of health inequality and well-being. Strazdins et al. (2010) found that poor quality jobs could pose a health risk to employed parents' children, such as more emotional and behavioral difficulties. Li et al. (2014) found parental work schedules link to four primary child developmental outcomes - internalizing and externalizing problems, cognitive development, and body mass index.

It is widely believed that the deteriorated labor market outcomes of baby boomers should have significantly affected the lives of their children generations (i.e., echo boomers) in many ways, aside from direct labor market outcomes (Flanagan and Eccles, 1993; Kaufman and Uhlenberg, 1998). This chapter provides a novel perspective that trade exposure may not only play a significant impact through the labor market as discussed above, but also delivers an inter-generational effect on the overall well-being of the younger generation that resides within the household. This research fills the gap by looking into the spillover effect on family members of those who are significantly impacted by the US-China trade liberalization. Specifically, this chapter answers two questions empirically. First, does trade liberalization have an effect on people's well-being status, especially the young adults. Second, do higher minimum wage and general social safety net alleviate the impact.

Following Mitra and Brucker (2014) and Dhongde and Haveman (2017), we employ the measure of multidimensional deprivation index of 5 dimensions - disability, education, health insurance, poverty, and employment status to estimate the influence of trade exposure on the well-being of different age-, race-, and gender groups. In particular, we are interested in young adults aged 17-24 who tend to be the children generation of the middle-aged population that is most heavily impacted by the US-China trade liberalization in 2001. Using Pierce and Schott's (2016, 2020) measure of trade liberalization exposure, we study multidimensional deprivation effects of trade liberalization with China across 1990-2013.

As the baseline estimation, we use the difference-in-difference identification strategy to examine multidimensional deprivation effects. The baseline results confirm our hypothesis that the young generation of 17-24 years old is the group that is most significantly affected. Moreover, the impact on males and females is of similar magnitude. Nonwhites are significantly deprived compared to white people. We also conduct intra-household dynamics regression, and the results suggest there may be an inter-generational spillover effect on the children generation's well-being.

Then we further explore if higher minimum wages help alleviate the deprivation impact. The welfare effects of minimum wage and government programs are mixed. Boadway and Cuff (2001) found that higher minimum wage can be welfare-improving and employment-enhancing, while Wu, Perloff, and Golan (2006) found that minimum wage, unlike most government transfer programs, lowered welfare in the 1980s and 1990s. To examine this effect specifically, we estimate a difference-in-difference-in-difference (triple-difference) model with two third-differences in the regression: the first is different minimum wages, and the second is different levels of social welfare spending. Results show that minimum wage may ease the negative impacts of trade exposure for select groups. In contrast, overall, the influence of minimum wage and the general social safety net is somewhat limited. A more comprehensive measure that accounts for health, income, education, insurance, etc., might be needed to help those who are multidimensionally deprived.

The remainder of the chapter proceeds as follows. Section 3.2 discusses the background and data used for the analyses. Section 3.3 presents the models and identification strategy, followed by Section 3.4, discussing the estimation results. Section 3.5 discusses the robustness of the results, and Section 3.6 concludes.

3.2 Data

3.2.1 Multi-Dimensional Deprivation

The primary well-being measure adopted in this chapter is Multidimensional Deprivation Index (MDI) by Dhongde and Haveman (2017). This measure is based on a methodology developed by Alkire and Foster (2011), which gained prominence due to its adoption by the United Nations (UN) in 2010 to estimate a global Multidimensional Poverty Index (UN-MPI). The Multidimensional Deprivation Index is in line with the UN's Sustainable Development Goals (SDGs), which proposes a multidimensional view of an individual's well-being depending on their capability of adequately functioning in one's society. It is ideal in this research as it extends the traditional single-dimensional poverty measure of income, expenditure, or wealth, and tracks an individual across multiple dimensions, and counts the number of deprivations simultaneously experienced by that individual.

We calculate MDI using the Current Population Survey's (CPS) Annual Social and Economic Supplement (ASEC), a nationally representative individual- and household-level data by the Census Bureau. CPS contains detailed information of each household member's demographic information, education, insurance status, and income, among other indicators.[1] Below is the description of the five dimensions we employed to construct the index:[2]

- *Standard of Living*: a person is considered deprived if he/she is part of a family whose income is below the threshold specified under the official poverty measure (OPM).[3]
- *Security*: if a person does not have any public or private insurance.[4]
- *Health Status*: an individual has work disability or reported income from disability benefits.[5]

[1] We restrict our sample to individuals who are older than 17 and exclude those who live in group quarters (group quarter classifies all housing units as falling into one of three main categories: households, group quarters, or vacant units).

[2] Our selection of the indicators is according to Mitra and Brucker (2014). Dhongde and Haveman (2017) constructed the index with six dimensions with an additional dimension of housing quality, which reports the number of persons per room in a housing unit. However, CPS does not provide information on that. Thus, the choice of indicators is restricted by the availability of data.

[3] Variable name: OFFPOV.

[4] Variables include "included in employer group health plan (inclugh)", "covered by Medicaid (himcaid)", "covered by Medicare (himcare)", "covered by military health insurance (hichamp)", "reported covered by private health insurance (phinsur)", "covered by group health insurance (covergh)", "covered by private health insurance (coverpi)".

[5] CPS collects disability-related variables of hearing, vision, remembering, physical, etc. However, these variables are only available onwards 2009.

- *Education*: an individual is considered deprived if he or she has less than a high school diploma.

- *Personal activities*: was unemployed in the past week.

We conducted our analysis at the MSA level. We calculate three multi-dimensional indices in each MSA. Let $i = 1, \ldots, n$ be the number of individuals and $j = 1, \ldots, d$ be the number of welfare dimensions. We assign g_{ij}^{m} equal to one if individual i in MSA m is deprived in dimension j and zero otherwise. We consider individual i is multidimensionally deprived if $\sum_{j=1}^{d} g_{ij}^{m}/d \geq 0.33$ (according to the UNDP-MPI's identification of multidimensional deprivation of an individual). In our case of $d = 5$, an individual deprived in two or more indicators is identified as multidimensionally deprived. Suppose that q individuals are identified as multidimensionally deprived in a given MSA. The first MDI in MSA m is equal to the proportion of deprived individuals in the population:

$$MDI^{m} = \frac{q}{n}$$

A drawback of MDI^{m} is that it does not capture the changes in intensity of deprivations, we provide the second measure - the average intensity index

$$A^{m} = \frac{1}{q} \sum_{j=1}^{d} g_{ij}/d$$

which represents the average number of deprivations for the multidimensionally deprived individuals. To capture both the proportion of deprived individuals and the intensity, the third measure - adjusted headcount index - is defined as the product of the first two measures

$$A * MDI = A^{m} \times MDI^{m} = \frac{1}{n} \sum_{j=1}^{d} g_{ij}/d$$

Using the above measures, we examine the MSA's multidimensional effects of trade liberalization with China.[6] We study these effects across several demographic attributes of age, gender, and race.

Table 3.1: CPS sample composition across time

	1990	2007	2013	Total
by age				
17-24	15.77%	14.60%	14.29%	14.40%
25-40	36.86%	30.95%	28.85%	31.80%
41-55	22.39%	30.27%	29.05%	28.15%
over 55	24.98%	24.18%	27.80%	25.65%
by sex				
male	48.08%	48.53%	48.38%	47.37%
female	51.92%	51.47%	51.62%	52.63%
by race				
White	83.74%	77.48%	75.64%	82.26%
Black	11.79%	13.25%	13.62%	10.71%
Asian	3.55%	5.99%	7.33%	4.57%
American Indian	0.45%	0.77%	0.79%	1.24%
other	0.48%	2.50%	2.61%	1.22%
No. of Obs	116,801	148,506	149,142	3,130,302
MSA	226	254	254	292

We use CPS data from 1990 to 2013. Our sample in 2007 includes 148,506 individuals who resided in 254 MSAs with trade liberalization exposure data. Table 3.1 shows the demographics of our samples. Young adults aged 17-24 account for 14.4% of the sample. Females account for 52.63% of the sample. In terms of ethnicity, White people account for 82.26% of the population while blacks represent 10.71%. The middle-class population account for the largest proportion of the sample, which is 51.92%.

Our variables of interest, summarized in Table 3.2, include three measures of the MDI index and each of the five dimensions[7] of the whole sample. Overall, the first measure (MDI) and the third measure (A*MDI) are about the equivalent magnitude, while the second measure (A) reports the lowest values. On a scale of 0 to 1, the adjusted headcount index (A*MDI) averages to be 15%. It means that the sample population is deprived in one

[6] MDI distribution in MSA in 2001 and 2007 are reported in Figure B.1 and Figure B.2.

[7] "no Insurance" in the table denotes no medical insurance.

Table 3.2: Summary statistics of CPS variables (means)

	1990	2007	2013	Total
MDI	0.22	0.16	0.17	0.18
	(0.09)	(0.07)	(0.07)	(0.08)
A	0.04	0.02	0.03	0.03
	(0.03)	(0.02)	(0.02)	(0.02)
A*MDI	0.19	0.13	0.13	0.15
	(0.04)	(0.04)	(0.04)	(0.05)
Disability	7.24%	7.93%	8.78%	8.02%
	(0.03)	(0.04)	(0.04)	(0.04)
No Insurance	12.64%	15.22%	14.85%	14.30%
	(0.07)	(0.07)	(0.07)	(0.07)
No Highschool	58.69%	19.04%	16.36%	30.31%
	(0.11)	(0.07)	(0.06)	(0.21)
Poverty	12.30%	11.99%	14.78%	13.05%
	(0.07)	(0.06)	(0.07)	(0.07)
Unemployment	3.64%	7.86%	10.37%	7.43%
	(0.02)	(0.03)	(0.04)	(0.04)

Note. No. of Observations: 15,407; MSA: 292

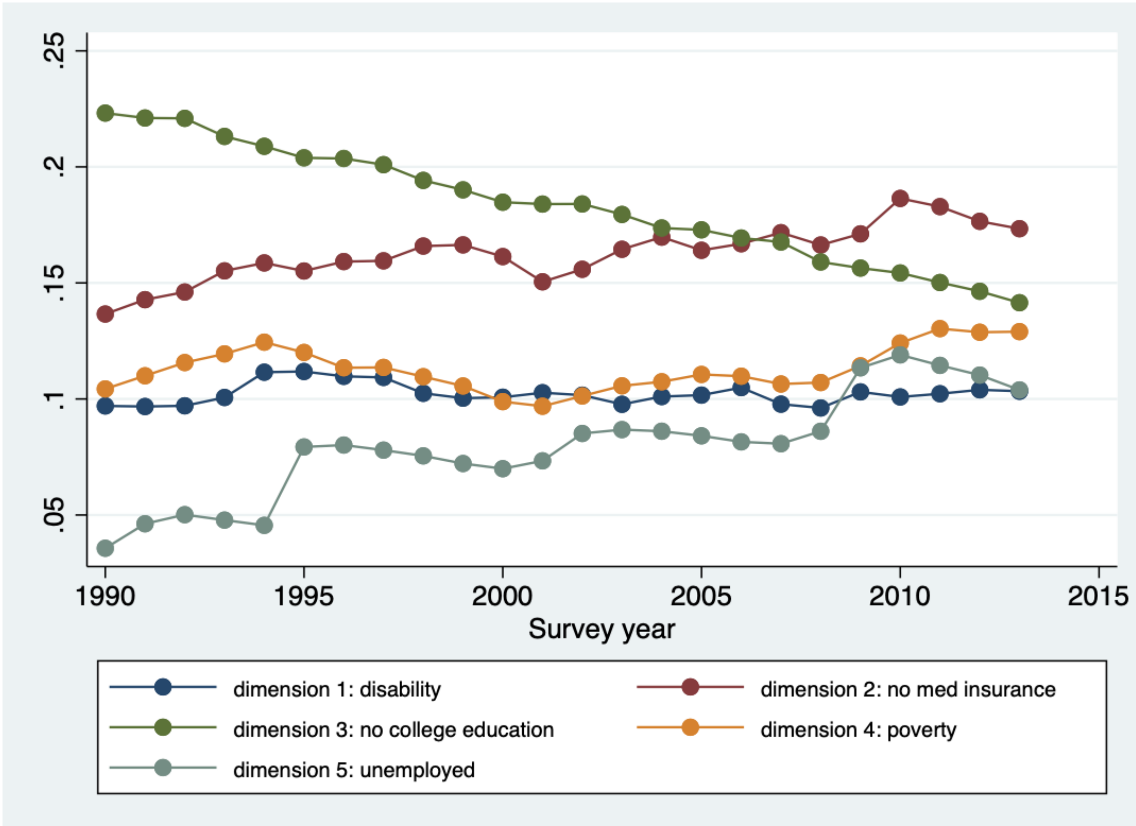
dimension on average. Between 1990 and 2013, we do not find variations in the intensity of deprivation (A), though the proportion of people who experienced deprivation (MDI) varied over time. In regard to each dimension, Figure 3.1 shows the extent of deprivation in each dimension. On average, about 10% of the population have more than one disability, 16% lack any form of medical insurance, 18% have no high school diploma, 11% of the population are below the poverty level, and 8% are unemployed.[8]

3.2.2 The NTR Gap

We follow Pierce and Schott (2016)'s methodology to measure a local labor market's exposure to trade liberalization. We start with their industry-level measure, $NTRGap_j$, defined as the difference between non-NTR rates and NTR rates in a six-digit NAICS sector j

$$NTRGap_j = non - NTRtariff_j - NTRtariff_j$$

[8]We also plot the percent of individuals deprived in ≥ 2 dimensions in Figure B.3.



Note. Values are given as percent of the population, 17-64 years

Figure 3.1: Extent of deprivation in each dimension

$NTRGap_j$ refers to the potential tariff increase on Chinese imports and captures the uncertainty faced by Chinese exporters in industry j. Pierce and Schott (2016) show that the elimination of trade uncertainty explains the sharp drop in US manufacturing employment. Using $NTRGap_j$, Pierce and Schott (2016) calculate a county's exposure to PNTR. We follow the same steps and calculate the exposure to PNTR for metropolitan areas:

$$NTRGap_m = \sum_j \frac{L_{jm}^{1990}}{L_m^{1990}} NTRGap_j$$

where L_{jm}^{1990} refers to the number of employees in sector j in MSA m in the year 1990, and L_m^{1990} refers to the total number of workers in MSA m.[9] In this chapter, higher $NTRGap_m$

[9]The information about employment weights, L_{jm}^{1990} and L_m^{1990}, are from the County Business Patterns (CBP), an annual dataset with information on employment and payroll by sector and county.

is assumed to indicate higher exposure of MSA m to trade liberalization with China. $NTRGap_m$ shows the distribution with the mean 0.145 and standard deviation 0.05.

3.3 Estimation Strategy

3.3.1 Identification Strategy

Our main estimation strategy follows Pierce and Schott (2016)'s baseline difference-in-differences (DID) specification:

$$\begin{aligned} LHS_{mt} &= \theta \cdot PostPNTR_t \times NTRGap_m + \beta \boldsymbol{X}_{mt} \\ &\quad + \gamma \cdot PostPNTR_t \times \boldsymbol{Z}_m + \delta_m + \delta_m + \varepsilon_{m,t}. \end{aligned} \tag{3.1}$$

The left-hand-side (LHS) variables, defined in year t and MSA m, include MDI^m,A^m, $A{*}MDI$, and five MDI dimensions of disability, insurance, highschool education, poverty, and unemployment. $\boldsymbol{X}_{mt}$ represents the (time-varying) overall US import tariff rate associated with the industries active in the MSA and the phasing out of the global Multi-Fiber Arrangement (MFA). $\boldsymbol{Z}_m$ represents the initial-period MSA attributes, the 1990 median household income, the 1990 share of the population without any college education, and the 1990 share of the population that are veterans. δ_m and δ_t refer to MSA and year fixed effects. We cluster standard errors at MSA levels. The sample period is 1990 to 2013.

The first term on the right-hand side is the DID term of interest, the interaction of a post-PNTR (i.e., $t > 2000$) indicator with the (time-invariant) MSA-level NTR Gap. The positive sign of θ implies that MSAs more exposed to PNTR (first difference) experience differential changes of LHS_{mt} after the change in US trade policy versus before (second difference)

$$\frac{\partial\left(E\left[LHS_{mt}|PostPNTR_t=1\right]-E\left[LHS_{mt}|PostPNTR_t=0\right]\right)}{\partial NTRGap_m} \tag{3.2}$$
$$= \theta.$$

Similarly, as in the second chapter, we employ triple-difference estimation to explore the effect of minimum wage on a more exposed region, specified as follows.

$$\begin{aligned} LHS_{mt} &= PostPNTR_t \times NTRGap_m \times (\mu_1 \cdot MW_m + \mu_2 \cdot SWE_m) \\ &+ PostPNTR_t \times (\theta \cdot NTRGap_m + \beta \cdot MW_m + \beta_2 \cdot SWE_m + \boldsymbol{Z}'_m \gamma) \\ &+ \boldsymbol{X}'_{mt}\lambda + \delta_m + \delta_t + \varepsilon_{mt}, \end{aligned} \tag{3.3}$$

where MW_m refers to the minimum wage of MSA m in year 2000, and we use the same LHS variables and control variables as in Equation 3.1. Here we also control various parameters of social welfare spending to account for confounding characteristics from finding an effect on minimum wage.[10] The first term on the right-hand side is the primary term of interest: a triple interaction of PostPNTR indicator, NTR Gap exposure, and the minimum wage of MSA m.

The implied impact of minimum wages can be derived by taking the slope of $NTRGap$ on LHS change with respect to $PostPNTR$, conditioning on MW_m :

$$\frac{\partial\left(E\left[LHS_{mt}|PostPNTR=1, MW_m\right]-E\left[LHS_{mt}|PostPNTR=0, MW_m\right]\right)}{\partial NTRGap_m}$$
$$= \theta + \mu_1 \, MW_m \tag{3.4}$$

Hence, the negative sign of μ_1 suggests that a higher minimum wage may mitigate the negative impacts of the trade shock.

[10]For minimum wages in multistate MSAs, we use the weighted average using population share and ASEC weights as CPS suggests.

3.4 Estimation Results

3.4.1 Difference-in-difference results

Baseline Results

In this section, we discuss the regression results for the entire sample. Table 3.3 reports estimates for θ in Equation 3.1 for the three deprivation indices (columns 1-3) and each of the five dimensions (columns 4-8). The difference-in-difference point estimates of interest are positive ($\theta > 0$) and statistically significant at conventional levels across all three MDI indices (MDI, A, A*MDI). The results confirm that PNTR does have a significant impact on the well-being of people. Those who live in more exposed regions have higher deprivation indices, meaning that they tend to be deprived of more dimensions than people who live in less PNTR-exposed areas. We then explore which of the five MDI dimensions drive changes in MDI indices. The estimates reported in columns 4-8 suggest that the increased deprivation level is mainly driven by disability, no medical insurance, poverty, and unemployment, with unemployment being the main contributor. Our estimation results are consistent with a series of previous studies on PNTR and labor market outcomes (Pierce and Schott, 2016, 2020; Brussevich, 2018), which indicate that trade liberalization with

Table 3.3: Baseline results

	MDI Index			Dimensions				
	MDI	A	A*MDI	Disability	NoInsurance	NoHighschool	Poverty	Unemployment
Post * NTR Gap	0.203***	0.101***	0.0517***	0.134***	0.0799*	-0.00209	0.122**	0.173***
	(0.0631)	(0.0312)	(0.0166)	(0.0480)	(0.0469)	(0.0519)	(0.0490)	(0.0363)
NTR rate	0.197	0.386	0.0982	1.392*	-0.565	0.767	-0.783	1.118*
	(1.062)	(0.550)	(0.303)	(0.806)	(0.914)	(0.970)	(0.853)	(0.674)
MFA rate	-1,013	8.255	-313.0	-1,852	3,182**	-873.1	183.4	-599.9
	(1,550)	(772.6)	(416.5)	(1,384)	(1,236)	(1,012)	(1,443)	(1,186)
Post * No College	-0.0622***	-0.0412***	-0.0220***	0.00379	0.00296	-0.223***	-0.0160	0.0258**
	(0.0219)	(0.0115)	(0.00585)	(0.0169)	(0.0163)	(0.0240)	(0.0234)	(0.0131)
Post * Veteran	0.147***	0.0776***	0.0489***	0.0501	0.100**	0.0827	0.108**	0.0464
	(0.0544)	(0.0273)	(0.0152)	(0.0483)	(0.0467)	(0.0597)	(0.0477)	(0.0293)
Post * Median HHI	-0.000342	-0.00597	0.00224	-0.0208*	-0.00351	-0.0107	0.0272***	-0.0220***
	(0.0106)	(0.00585)	(0.00265)	(0.0108)	(0.00977)	(0.0106)	(0.0102)	(0.00698)
Observations	4,660	4,660	4,660	4,660	4,660	4,660	4,660	4,660
R^2	0.651	0.725	0.691	0.356	0.621	0.894	0.492	0.572

Note. Standard errors clustered on MSAs in parentheses, MSA and year fixed effects.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

China has brought significant labor market disruptions. Industries/regions more exposed to the change experienced greater employment loss, higher mortality rate, and crime rate. This chapter confirms the results and further provides a channel of influence. The results on MDI indices suggest that the exposed workers experienced multidimensional deprivations, leading to significantly decreased well-being levels, which may induce other serious outcomes, such as crime, drug, mortality, etc.

Results on Age

Our main question is to understand whether there is an inter-generational effect on the young people, which may be a spillover effect from their parent generation's job displacement. We then estimate θ in Equation 3.1 on age groups of 17-24, 25-40, 41-55, and over 56 years old, and report the results in Table 3.4.[11]

Overall, an MSA with higher exposure to PNTR shows higher levels of MDI for age groups 17-24, 25-40, and over 56. The largest magnitude is on people aged 17-24, while 25-40 and over 56 year-olds are about the same magnitude. According to the sample year, the 17-24 sample tend to be echo boomers, and those aged over 56 are baby boomers, who are usually the parents of echo boomers. The results show significantly positive estimates for θ in MDIs, and the absolute values of estimates are even larger than the ones of the baby boomers. The welfare loss for the middle-aged group, baby boomers, are well reported (Pierce and Schott, 2020). However, it is surprising that the young generations, echo boomers, are also significantly affected. These results may suggest that there are inter-generational spillover effects - parents' job status and well-being may significantly impact their children's lives.

We then look at the change of each welfare dimension to better understand the young generation's welfare loss. Columns 4-8 in Table 3.4 show the estimates. Age group 17-

[11] We use different age group classifications from Chapter 2 since we are interested to know different generation's MDI impact. Age classification of 17-24 is widely used to define young adulthood, age 25-40 as early middle age, 41-55 as middle age, and over 56 as the elderly.

Table 3.4: Age results

(a) Age 17-24

	MDI Index			Dimensions				
	MDI	A	A*MDI	Disability	NoInsurance	NoHighschool	Poverty	Unemployment
Post * NTR Gap	0.357***	0.189***	0.124***	0.0758**	0.0235	0.474***	0.236**	0.133**
	(0.123)	(0.0538)	(0.0400)	(0.0353)	(0.118)	(0.144)	(0.0947)	(0.0620)
NTR rate	-1.320	-0.701	-0.393	0.300	-3.468	2.599	-2.439	-0.496
	(2.626)	(1.097)	(0.884)	(0.647)	(2.186)	(2.697)	(1.936)	(1.152)
MFA rate	-3,127	-750.0	-1,254	564.8	-913.6	-3,296	2,796	-2,900
	(3,027)	(1,496)	(1,049)	(1,072)	(2,975)	(4,079)	(2,962)	(2,718)
Post * No College	0.0221	0.00268	0.00339	0.00197	0.0165	-0.0825	0.0520	0.0254
	(0.0548)	(0.0220)	(0.0179)	(0.0181)	(0.0487)	(0.0591)	(0.0439)	(0.0311)
Post * Veteran	0.0786	0.0194	0.00728	0.0158	0.158	-0.0669	0.00591	-0.0164
	(0.134)	(0.0588)	(0.0469)	(0.0360)	(0.130)	(0.138)	(0.0990)	(0.0711)
Post * Median HHI	0.0454	0.0154	0.0180*	-0.00657	0.00475	0.00555	0.0692***	0.00388
	(0.0300)	(0.0121)	(0.00982)	(0.00870)	(0.0285)	(0.0270)	(0.0188)	(0.0158)
Observations	4,658	4,658	4,658	4,658	4,658	4,658	4,658	4,658
R^2	0.307	0.348	0.334	0.099	0.295	0.433	0.255	0.148

(b) Age 25-40

	MDI Index			Dimensions				
	MDI	A	A*MDI	Disability	NoInsurance	NoHighschool	Poverty	Unemployment
Post * NTR Gap	0.167**	0.109***	0.0471**	0.0921**	0.118*	-0.0701	0.154*	0.252***
	(0.0713)	(0.0392)	(0.0186)	(0.0359)	(0.0648)	(0.0685)	(0.0831)	(0.0458)
NTR rate	-1.158	0.0669	-0.0937	0.524	-1.257	-0.365	-0.393	1.825**
	(1.506)	(0.768)	(0.393)	(0.779)	(1.238)	(1.565)	(1.289)	(0.853)
MFA rate	358.3	1,033	346.4	-933.5	4,629*	1,214	1,662	-1,406
	(3,029)	(1,583)	(939.5)	(1,314)	(2,775)	(2,535)	(2,772)	(1,349)
Post * No College	-0.0498	-0.0362**	-0.0137	0.0112	0.00386	-0.227***	0.00419	0.0271
	(0.0333)	(0.0171)	(0.00887)	(0.0145)	(0.0284)	(0.0300)	(0.0345)	(0.0201)
Post * Veteran	0.152*	0.0940**	0.0440*	0.0619	0.134	0.138	0.150**	-0.0144
	(0.0834)	(0.0426)	(0.0232)	(0.0379)	(0.0840)	(0.0840)	(0.0725)	(0.0459)
Post * Median HHI	-0.00192	-0.00390	0.00125	-0.0206***	-0.0184	-0.00893	0.0419***	-0.0135
	(0.0153)	(0.00827)	(0.00370)	(0.00705)	(0.0157)	(0.0142)	(0.0153)	(0.00992)
Observations	4,660	4,660	4,660	4,660	4,660	4,660	4,660	4,660
R^2	0.471	0.553	0.487	0.175	0.481	0.792	0.363	0.311

(c) Age 41-55

	MDI Index			Dimensions				
	MDI	A	A*MDI	Disability	NoInsurance	NoHighschool	Poverty	Unemployment
Post * NTR Gap	0.151*	0.0482	0.0242	0.0632	0.0884	-0.209***	0.152**	0.146**
	(0.0808)	(0.0444)	(0.0191)	(0.0538)	(0.0703)	(0.0638)	(0.0724)	(0.0645)
NTR rate	-0.437	-0.0278	-0.285	-0.270	0.424	-0.623	-0.422	0.752
	(1.401)	(0.827)	(0.401)	(1.086)	(1.209)	(1.434)	(1.116)	(1.122)
MFA rate	289.4	714.0	434.9	559.5	4,868**	572.4	-2,258	-171.7
	(2,509)	(1,294)	(677.6)	(1,814)	(2,373)	(2,583)	(1,387)	(1,901)
Post * No College	-0.0405	-0.0267*	-0.0112	0.0144	0.00965	-0.186***	-0.00826	0.0366*
	(0.0310)	(0.0143)	(0.00813)	(0.0232)	(0.0270)	(0.0301)	(0.0244)	(0.0209)
Post * Veteran	0.159**	0.101***	0.0513**	0.0854	0.119*	0.142*	0.0265	0.133***
	(0.0741)	(0.0372)	(0.0203)	(0.0581)	(0.0635)	(0.0766)	(0.0538)	(0.0501)
Post * Median HHI	-0.00671	-0.00444	0.00174	-0.0124	0.00959	0.0114	-0.00358	-0.0273**
	(0.0165)	(0.00750)	(0.00410)	(0.0123)	(0.0128)	(0.0150)	(0.0106)	(0.0109)
Observations	4,660	4,660	4,660	4,660	4,660	4,660	4,660	4,660
R^2	0.460	0.550	0.481	0.205	0.440	0.805	0.332	0.426

(d) Age over 56

	MDI Index			Dimensions				
	MDI	A	A*MDI	Disability	NoInsurance	NoHighschool	Poverty	Unemployment
Post * NTR Gap	0.191**	0.0738*	0.0518**	0.169	0.0603	-0.0363	0.0317	0.145***
	(0.0830)	(0.0436)	(0.0253)	(0.116)	(0.0472)	(0.0973)	(0.0567)	(0.0516)
NTR rate	3.094*	1.671*	0.914*	3.481*	1.327*	2.148	-0.188	1.587*
	(1.644)	(0.852)	(0.497)	(2.082)	(0.749)	(1.627)	(1.063)	(0.954)
MFA rate	-2,739	-1,056	-1,213*	-3,601	1,050	-1,887	-1,312	467.6
	(1,816)	(1,074)	(623.1)	(2,977)	(1,234)	(3,098)	(1,625)	(1,668)
Post * No College	-0.100***	-0.0556***	-0.0407***	0.0295	-0.0121	-0.251***	-0.0607***	0.0158
	(0.0380)	(0.0213)	(0.0120)	(0.0494)	(0.0199)	(0.0555)	(0.0229)	(0.0185)
Post * Veteran	0.160*	0.0629	0.0685**	0.0928	-0.0218	0.0965	0.107*	0.0402
	(0.0906)	(0.0470)	(0.0279)	(0.122)	(0.0412)	(0.116)	(0.0565)	(0.0473)
Post * Median HHI	0.000427	-0.0132	0.00389	-0.00635	-0.00630	-0.0305	0.00610	-0.0291***
	(0.0235)	(0.0125)	(0.00755)	(0.0323)	(0.0100)	(0.0270)	(0.0110)	(0.00958)
Observations	4,660	4,660	4,660	4,660	4,660	4,660	4,660	4,660
R^2	0.476	0.598	0.525	0.244	0.279	0.822	0.278	0.438

Note. Standard errors clustered on MSAs in parentheses, MSA and year fixed effects.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

24 shows that the MDI changes are mostly driven by higher rates of disability, no high school diploma, poverty, and unemployment. The results provide another perspective that the welfare loss of the younger generation does not solely come from labor market outcomes. In an MSA with higher exposure to trade liberalization, the younger generation faced higher chances of highschool dropouts, poverty, and disability payment. We believe that non-labor market outcomes could play an even larger role than labor market outcomes for younger generations since these dimensions may affect their future incomes. Notably, high school education deprivation came out as the main driver among the five dimensions. Education has long been shown as an effective way for poverty alleviation and to increase individual's well-being level (Aduke et al., 2012; Hilal, 2012), especially for younger adults (Chaudhry et al., 2010; Selyutin et al., 2017). Understanding the MDI influencing channel to young adults is crucial since young adulthood aged 17-24 is a critical developmental period, bridging adolescence and independent adulthood. Life experience during these years has profound and long-lasting implications for their future economic security, health, and well-being (Council et al., 2015). Increasing young adults' education, as this chapter suggests, may significantly increase their well-being level.

The results also suggest that unemployment came out as the main driver for age 25-40, 41-55, and age over 65. Unlike results on younger adults on 17-24, middle-aged people suffer from unemployment significantly due to PNTR, leading to decreased well-being level. This pattern may suggest their unemployment-originated decreased well-being level may affect the well-being of their children living within the same household, leading to the younger generation being deprived of highschool education and being in poverty. We are going to take a closer look at this pattern in the section *Intra-household Dynamics*.

Results on Gender

In this section, we further explore our results by gender and compare variations by age. Table 3.5 reports results for males and females.

Table 3.5: Gender results

(a) Male

	MDI Index			Dimensions				
	MDI	A	A*MDI	Disability	NoInsurance	NoHighschool	Poverty	Unemployment
Post * NTR Gap	0.188**	0.103***	0.0522***	0.119**	0.140**	0.000863	0.0875	0.178***
	(0.0764)	(0.0385)	(0.0193)	(0.0589)	(0.0542)	(0.0608)	(0.0576)	(0.0462)
NTR rate	0.302	0.569	0.158	1.167	-0.699	1.522	-0.889	1.741**
	(1.199)	(0.592)	(0.334)	(0.951)	(1.100)	(1.091)	(0.914)	(0.822)
MFA rate	-2,390	-249.1	-574.1	-1,604	2,519*	-805.7	91.64	-1,446
	(1,682)	(857.7)	(429.3)	(1,363)	(1,349)	(1,291)	(1,280)	(1,413)
Post * No College	-0.0577**	-0.0434***	-0.0186***	-0.000994	0.00535	-0.233***	-0.00740	0.0190
	(0.0257)	(0.0132)	(0.00660)	(0.0207)	(0.0213)	(0.0253)	(0.0241)	(0.0154)
Post * Veteran	0.152**	0.0793**	0.0471***	-0.00493	0.123**	0.133*	0.112**	0.0329
	(0.0624)	(0.0305)	(0.0165)	(0.0530)	(0.0592)	(0.0690)	(0.0460)	(0.0387)
Post * Median HHI	-0.00336	-0.00633	0.00136	-0.0188*	0.00209	-0.0119	0.0266**	-0.0297***
	(0.0132)	(0.00682)	(0.00340)	(0.0112)	(0.0119)	(0.0117)	(0.0121)	(0.00923)
Observations	4,660	4,660	4,660	4,660	4,660	4,660	4,660	4,660
R^2	0.546	0.637	0.598	0.296	0.517	0.831	0.408	0.453

(b) Female

	MDI Index			Dimensions				
	MDI	A	A*MDI	Disability	NoInsurance	NoHighschool	Poverty	Unemployment
Post * NTR Gap	0.218***	0.100***	0.0527***	0.143***	0.0280	0.00493	0.148***	0.165***
	(0.0609)	(0.0301)	(0.0164)	(0.0495)	(0.0546)	(0.0554)	(0.0498)	(0.0355)
NTR rate	0.0511	0.204	0.0104	1.523*	-0.404	0.238	-0.860	0.521
	(1.133)	(0.590)	(0.317)	(0.872)	(0.954)	(1.054)	(0.952)	(0.723)
MFA rate	443.1	313.9	-44.31	-2,170	3,938**	-896.5	530.3	168.1
	(1,804)	(883.6)	(501.2)	(1,775)	(1,677)	(1,229)	(1,778)	(1,185)
Post * No College	-0.0679***	-0.0397***	-0.0253***	0.00555	0.00287	-0.213***	-0.0258	0.0317**
	(0.0235)	(0.0122)	(0.00646)	(0.0187)	(0.0178)	(0.0289)	(0.0251)	(0.0142)
Post * Veteran	0.145**	0.0776**	0.0507***	0.109*	0.0734	0.0432	0.103*	0.0597*
	(0.0622)	(0.0312)	(0.0176)	(0.0610)	(0.0473)	(0.0678)	(0.0571)	(0.0342)
Post * Median HHI	0.000952	-0.00604	0.00249	-0.0224*	-0.00790	-0.0107	0.0252**	-0.0144**
	(0.0102)	(0.00564)	(0.00255)	(0.0126)	(0.00960)	(0.0115)	(0.0101)	(0.00661)
Observations	4,660	4,660	4,660	4,660	4,660	4,660	4,660	4,660
R^2	0.610	0.699	0.666	0.272	0.588	0.882	0.453	0.491

Note. Standard errors clustered on MSAs in parentheses, MSA and year fixed effects.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 3.6: Male results by age

(a) Age 17-24

	MDI Index			Dimensions				
	MDI	A	A*MDI	Disability	NoInsurance	NoHighschool	Poverty	Unemployment
Post * NTR Gap	0.321**	0.203***	0.138**	0.0330	0.236*	0.467***	0.181	0.101
	(0.154)	(0.0617)	(0.0538)	(0.0532)	(0.131)	(0.156)	(0.121)	(0.0913)
NTR rate	-0.294	0.0126	0.618	0.182	-3.883	6.535**	-3.459	0.688
	(2.704)	(1.129)	(1.048)	(0.950)	(2.481)	(2.713)	(2.682)	(1.644)
MFA rate	-11,626***	-3,650*	-3,615**	2,004	-4,137	-7,518	-630.9	-7,968**
	(4,167)	(2,145)	(1,556)	(1,650)	(4,547)	(6,032)	(2,497)	(3,798)
Post * No College	0.123*	0.0287	0.0423	0.0271	0.0442	-0.0485	0.0792	0.0413
	(0.0696)	(0.0285)	(0.0290)	(0.0323)	(0.0670)	(0.0697)	(0.0488)	(0.0450)
Post * Veteran	0.133	0.0191	-0.00258	0.0252	0.170	-0.0799	0.0181	-0.0375
	(0.186)	(0.0797)	(0.0781)	(0.0593)	(0.180)	(0.180)	(0.128)	(0.108)
Post * Median HHI	0.0531	0.0181	0.0288*	0.00928	-0.00343	0.0185	0.0754***	-0.00928
	(0.0378)	(0.0157)	(0.0153)	(0.0152)	(0.0350)	(0.0350)	(0.0226)	(0.0229)
Observations	4,652	4,652	4,652	4,652	4,652	4,652	4,652	4,652
R^2	0.204	0.245	0.214	0.090	0.211	0.293	0.181	0.104

(b) Age 25-40

	MDI Index			Dimensions				
	MDI	A	A*MDI	Disability	NoInsurance	NoHighschool	Poverty	Unemployment
Post * NTR Gap	0.182*	0.119**	0.0610**	0.113*	0.151	0.00697	0.0544	0.270***
	(0.106)	(0.0601)	(0.0284)	(0.0617)	(0.0994)	(0.0872)	(0.0911)	(0.0746)
NTR rate	-1.553	-0.0390	-0.0645	0.553	-2.853	1.334	-1.598	2.368*
	(1.762)	(0.888)	(0.479)	(0.978)	(1.750)	(1.553)	(1.426)	(1.216)
MFA rate	-92.42	628.4	-277.8	-1,479	6,169*	-916.6	1,473	-2,105
	(3,403)	(1,722)	(1,037)	(2,157)	(3,583)	(3,410)	(3,178)	(1,901)
Post * No College	-0.0622	-0.0449**	-0.0143	-0.000140	0.0234	-0.259***	-0.0137	0.0250
	(0.0417)	(0.0222)	(0.0120)	(0.0230)	(0.0421)	(0.0347)	(0.0333)	(0.0281)
Post * Veteran	0.131	0.0912	0.0439	0.0308	0.103	0.212*	0.136*	-0.0263
	(0.106)	(0.0582)	(0.0331)	(0.0639)	(0.103)	(0.109)	(0.0739)	(0.0724)
Post * Median HHI	-0.00349	-0.00298	0.000978	-0.0170*	0.00424	-0.0274	0.0416**	-0.0164
	(0.0209)	(0.0114)	(0.00618)	(0.0102)	(0.0226)	(0.0188)	(0.0169)	(0.0145)
Observations	4,660	4,660	4,660	4,660	4,660	4,660	4,660	4,660
R^2	0.335	0.430	0.342	0.141	0.357	0.697	0.252	0.226

(c) Age 41-55

	MDI Index			Dimensions				
	MDI	A	A*MDI	Disability	NoInsurance	NoHighschool	Poverty	Unemployment
Post * NTR Gap	0.117	0.0410	0.0228	0.0640	0.119	-0.258***	0.140*	0.140
	(0.101)	(0.0555)	(0.0231)	(0.0769)	(0.0914)	(0.0779)	(0.0827)	(0.0850)
NTR rate	0.444	0.428	-0.0201	-0.440	1.377	-0.646	0.0999	1.750
	(1.810)	(0.967)	(0.444)	(1.539)	(1.576)	(1.749)	(1.218)	(1.299)
MFA rate	-562.2	136.6	623.8	-782.7	3,598	1,512	-2,210	-1,434
	(2,965)	(1,786)	(917.3)	(2,599)	(2,942)	(4,041)	(1,502)	(2,713)
Post * No College	-0.0820**	-0.0467**	-0.0199*	-0.0155	-0.00499	-0.219***	-0.0149	0.0205
	(0.0395)	(0.0184)	(0.0108)	(0.0286)	(0.0400)	(0.0345)	(0.0280)	(0.0253)
Post * Veteran	0.213**	0.139***	0.0692***	0.0843	0.148*	0.175	0.126*	0.159***
	(0.0993)	(0.0501)	(0.0250)	(0.0867)	(0.0790)	(0.106)	(0.0646)	(0.0594)
Post * Median HHI	-0.0238	-0.0112	-0.00465	-0.0183	0.00889	-0.00711	-0.00760	-0.0321**
	(0.0214)	(0.0104)	(0.00574)	(0.0162)	(0.0192)	(0.0189)	(0.0130)	(0.0143)
Observations	4,660	4,660	4,660	4,660	4,660	4,660	4,660	4,660
R^2	0.342	0.420	0.354	0.153	0.327	0.665	0.246	0.304

(d) Age over 56

	MDI Index			Dimensions				
	MDI	A	A*MDI	Disability	NoInsurance	NoHighschool	Poverty	Unemployment
Post * NTR Gap	0.107	0.0375	0.0163	0.118	0.136**	-0.0894	-0.0450	0.0682
	(0.0961)	(0.0525)	(0.0265)	(0.139)	(0.0585)	(0.125)	(0.0682)	(0.0655)
NTR rate	2.838*	1.674**	0.736	3.262	2.173**	1.308	0.00860	1.619
	(1.566)	(0.826)	(0.486)	(2.253)	(0.995)	(1.841)	(1.124)	(1.050)
MFA rate	-855.9	792.5	-577.7	-1,615	1,028	1,042	1,018	2,489
	(2,517)	(1,468)	(807.9)	(3,441)	(1,635)	(3,732)	(2,006)	(2,402)
Post * No College	-0.0992**	-0.0527**	-0.0275**	0.0185	-0.0179	-0.269***	-0.0186	0.0231
	(0.0418)	(0.0254)	(0.0133)	(0.0471)	(0.0200)	(0.0791)	(0.0294)	(0.0224)
Post * Veteran	0.101	0.0132	0.0450	-0.0970	0.0176	0.204	0.0244	-0.0830
	(0.0974)	(0.0522)	(0.0288)	(0.119)	(0.0511)	(0.153)	(0.0688)	(0.0565)
Post * Median HHI	-0.000963	-0.0112	0.00308	-0.00661	-0.0163	-0.00864	0.00910	-0.0336***
	(0.0208)	(0.0132)	(0.00733)	(0.0273)	(0.0109)	(0.0387)	(0.0154)	(0.0106)
Observations	4,660	4,660	4,660	4,660	4,660	4,660	4,660	4,660
R^2	0.320	0.445	0.361	0.176	0.188	0.703	0.174	0.287

Note. Standard errors clustered on MSAs in parentheses, MSA and year fixed effects.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 3.7: Female results by age

(a) Age 17-24

	MDI Index			Dimensions				
	MDI	A	A*MDI	Disability	NoInsurance	NoHighschool	Poverty	Unemployment
Post * NTR Gap	0.398***	0.171**	0.132***	0.109**	-0.180	0.524***	0.251**	0.151**
	(0.143)	(0.0671)	(0.0500)	(0.0496)	(0.140)	(0.157)	(0.127)	(0.0767)
NTR rate	-2.336	-1.317	-1.161	0.658	-3.651	0.309	-2.229	-1.674
	(3.336)	(1.380)	(1.328)	(0.978)	(2.743)	(4.013)	(2.309)	(1.634)
MFA rate	4,360	1,844	1,614	-514.3	4,453	-2,527	5,747	2,060
	(4,957)	(2,325)	(2,010)	(1,527)	(3,204)	(4,580)	(4,784)	(2,650)
Post * No College	-0.108*	-0.0381	-0.0444**	-0.0317*	-0.0137	-0.160***	0.0193	-0.00472
	(0.0598)	(0.0252)	(0.0198)	(0.0190)	(0.0553)	(0.0601)	(0.0543)	(0.0337)
Post * Veteran	0.00103	-0.00109	-0.00977	-0.0178	0.0614	0.0281	-0.0412	-0.0360
	(0.144)	(0.0620)	(0.0470)	(0.0436)	(0.126)	(0.138)	(0.125)	(0.0777)
Post * Median HHI	0.0231	0.0120	0.0120	-0.0141*	0.00388	-0.0185	0.0620***	0.0269
	(0.0309)	(0.0135)	(0.0108)	(0.00829)	(0.0295)	(0.0288)	(0.0234)	(0.0179)
Observations	4,652	4,652	4,652	4,652	4,652	4,652	4,652	4,652
R^2	0.241	0.266	0.258	0.070	0.213	0.317	0.190	0.109

(b) Age 25-40

	MDI Index			Dimensions				
	MDI	A	A*MDI	Disability	NoInsurance	NoHighschool	Poverty	Unemployment
Post * NTR Gap	0.148**	0.0997***	0.0421**	0.0688	0.0507	-0.122	0.262***	0.238***
	(0.0677)	(0.0338)	(0.0200)	(0.0459)	(0.0808)	(0.0845)	(0.0928)	(0.0392)
NTR rate	-1.314	-0.0570	-0.269	0.266	-0.609	-1.894	0.549	1.403*
	(1.699)	(0.842)	(0.445)	(1.048)	(1.312)	(1.923)	(1.570)	(0.826)
MFA rate	781.6	1,599	489.2	-253.2	3,449	3,399	1,901	-498.8
	(3,494)	(1,857)	(1,017)	(1,921)	(3,303)	(3,132)	(2,978)	(1,846)
Post * No College	-0.0379	-0.0290	-0.0114	0.0220	-0.0100	-0.209***	0.0201	0.0315
	(0.0358)	(0.0177)	(0.0103)	(0.0192)	(0.0334)	(0.0354)	(0.0425)	(0.0219)
Post * Veteran	0.181**	0.101**	0.0437*	0.0746	0.174*	0.102	0.168*	-0.0128
	(0.0882)	(0.0408)	(0.0254)	(0.0544)	(0.0972)	(0.0863)	(0.0942)	(0.0520)
Post * Median HHI	-0.00394	-0.00620	-7.49e-05	-0.0238**	-0.0388**	0.000256	0.0383**	-0.00694
	(0.0138)	(0.00720)	(0.00355)	(0.0103)	(0.0158)	(0.0149)	(0.0171)	(0.0108)
Observations	4,660	4,660	4,660	4,660	4,660	4,660	4,660	4,660
R^2	0.402	0.489	0.418	0.105	0.428	0.748	0.321	0.225

(c) Age 41-55

	MDI Index			Dimensions				
	MDI	A	A*MDI	Disability	NoInsurance	NoHighschool	Poverty	Unemployment
Post * NTR Gap	0.164*	0.0501	0.0232	0.0527	0.110	-0.204**	0.157**	0.135**
	(0.0921)	(0.0499)	(0.0248)	(0.0661)	(0.0834)	(0.0813)	(0.0788)	(0.0658)
NTR rate	-1.664	-0.595	-0.654	-0.382	-0.0691	-0.996	-1.123	-0.408
	(1.702)	(1.016)	(0.556)	(1.412)	(1.403)	(1.680)	(1.301)	(1.476)
MFA rate	1,155	1,015	123.8	1,557	5,545**	-42.06	-2,772	789.8
	(2,883)	(1,401)	(736.2)	(1,643)	(2,812)	(2,223)	(1,914)	(2,058)
Post * No College	0.000357	-0.00312	-0.00165	0.0358	0.0314	-0.134***	-0.00169	0.0533*
	(0.0362)	(0.0170)	(0.00986)	(0.0298)	(0.0350)	(0.0424)	(0.0278)	(0.0271)
Post * Veteran	0.133	0.0718	0.0447	0.103	0.0961	0.0766	-0.0464	0.130*
	(0.0985)	(0.0482)	(0.0281)	(0.0723)	(0.0864)	(0.0896)	(0.0648)	(0.0689)
Post * Median HHI	0.0101	0.00240	0.00737*	-0.00760	0.0113	0.0319*	0.000378	-0.0240**
	(0.0174)	(0.00755)	(0.00418)	(0.0125)	(0.0179)	(0.0184)	(0.0118)	(0.0110)
Observations	4,659	4,659	4,659	4,659	4,659	4,659	4,659	4,659
R^2	0.374	0.486	0.408	0.153	0.382	0.785	0.266	0.328

(d) Age over 56

	MDI Index			Dimensions				
	MDI	A	A*MDI	Disability	NoInsurance	NoHighschool	Poverty	Unemployment
Post * NTR Gap	0.227**	0.0972**	0.0711**	0.203	0.0161	0.00614	0.0683	0.193***
	(0.0990)	(0.0483)	(0.0330)	(0.131)	(0.0554)	(0.104)	(0.0707)	(0.0609)
NTR rate	2.944	1.605	0.899	3.775*	0.642	2.747	-0.346	1.208
	(1.986)	(1.004)	(0.603)	(2.253)	(0.871)	(1.967)	(1.372)	(1.163)
MFA rate	-3,423	-2,205	-1,418*	-5,089	674.0	-2,714	-2,621	-1,273
	(2,740)	(1,585)	(830.6)	(4,312)	(1,356)	(3,577)	(2,265)	(1,897)
Post * No College	-0.0901*	-0.0571**	-0.0469***	0.0282	-0.00211	-0.241***	-0.0822***	0.0113
	(0.0466)	(0.0234)	(0.0150)	(0.0609)	(0.0228)	(0.0579)	(0.0265)	(0.0238)
Post * Veteran	0.209*	0.106*	0.0903**	0.237	-0.0428	0.0387	0.157**	0.140**
	(0.123)	(0.0572)	(0.0389)	(0.156)	(0.0537)	(0.128)	(0.0669)	(0.0646)
Post * Median HHI	0.00109	-0.0156	0.00328	-0.00848	0.00274	-0.0503*	0.00592	-0.0277**
	(0.0298)	(0.0142)	(0.00947)	(0.0399)	(0.0108)	(0.0263)	(0.0121)	(0.0134)
Observations	4,660	4,660	4,660	4,660	4,660	4,660	4,660	4,660
R^2	0.410	0.543	0.463	0.195	0.244	0.793	0.254	0.362

Note. Standard errors clustered on MSAs in parentheses, MSA and year fixed effects.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Overall, both male and female estimates turn out to be significantly positive, and the magnitudes do not differ very much. The results suggest that both males and females experienced significant multidimensional deprivation due to PNTR. When we take a deeper dive into the dimensions, the results suggest different channels of influence. For males, the main driving forces are disability, lack of medical insurance, and unemployment, with the magnitude of unemployment being the largest. In contrast, for females, the main driving forces are disability, poverty, and unemployment.

Males are the main population who got displaced from their original work, as studied in Pierce and Schott (2016, 2020). Results here suggest that loss of medical insurance coverage may also contribute to a male's well-being status. It is more or less related to unemployment status since medical insurance coverage is usually required/provided by employers. Especially when the loss of medical insurance is combined with disability status, maintaining their original well-being status may solely depend on the possibility of social insurance programs. Concerning females, PNTR significantly increased their unemployment, poverty level, and disability status, leading to increased multidimensional deprivation. These results may be explained by Besedeš, Lee, and Yang (2021), who found trade liberalization increased female workers' unemployment rate while their employment rate remained unchanged. Concurrently, both male and female spent less overall time working. The deteriorated labor market conditions for both male and female induced a series of changes in welfare dimensions, which may ultimately lead to well-being deprivation.

Table 3.6 and Table 3.7 further report male results by age and female results by age respectively. For males, MDI measures for both age 17-24 and age 25-40 turn out significant, while the magnitudes on the younger adult of 17-24 are the largest. The contributing dimensions for MDIs are different for these two age groups. For 17-24, no medical insurance and highschool education deprivation are the main driving forces, while for age 25-40, disability and unemployment are significant. These results present a clear picture that even though younger adults and middle-aged population are experiencing overall well-being reduction, the reduction of younger adults mainly comes from non-labor market dimensions. At the same time, labor-market-related factors mainly drive that of middle-aged people. This pattern may be due to the social characteristics of different age groups and may be related to their different roles played within the household.

Results on female show that age groups of 17-24, 25-40, and age over 56's deprivation measures are significant, while younger adults aged 17-24 still show the largest magnitude. The driving forces for age 17-24 include disability, no highschool diploma, poverty, and unemployment, with no highschool diploma being the main driving force. In comparison, females tend to have a higher probability of being in poverty in the presence of income shocks due to different characteristics in vulnerability, labor productivity, social networks, and education, etc. (Devereux, 2002; Philip and Rayhan, 2004).

Results on Race

In this section, we explore results on race. We separately report our estimates on whites and nonwhites in Table 3.8. Results on both white and nonwhite are significant, while the nonwhite population experienced a larger PNTR-induced deprivation than the white population. The driving forces for whites are mainly disability and unemployment, and that of the nonwhite people are disability, poverty, and unemployment. The MDI results may suggest a different pattern as studied in similar papers. Pierce and Schott (2020) showed PNTR induced larger socio-economic effects for white males since they are the main population who are working in the sectors with higher trade exposure, such as manufacturing. Therefore, we expect a larger magnitude for white people in this section. The differences in these results confirm that MDI measures capture multiple dimensions besides work-related parameters. Various socio-economic indicators such as medical insurance coverage, education, poverty status, and disability all enter into the dimensions of MDI indices, which play significant roles. Danziger et al. (1982) found a substantially higher increase in poverty in nonwhites than whites given benefit reduction and lack of labor market opportunity.

Table 3.8: Race results

(a) White

	MDI Index			Dimensions				
	MDI	A	A*MDI	Disability	NoInsurance	NoHighschool	Poverty	Unemployment
Post * NTR Gap	0.142**	0.0654**	0.0374**	0.122**	0.0531	-0.0504	0.0651	0.137***
	(0.0646)	(0.0321)	(0.0159)	(0.0504)	(0.0481)	(0.0514)	(0.0465)	(0.0360)
NTR rate	0.380	0.314	0.149	1.398*	-0.492	0.654	-0.796	0.804
	(0.951)	(0.505)	(0.260)	(0.827)	(0.923)	(0.961)	(0.779)	(0.609)
MFA rate	345.5	700.8	-17.05	-1,726	4,370***	-434.9	1,256	38.97
	(1,606)	(814.5)	(415.0)	(1,518)	(1,372)	(1,148)	(1,807)	(1,162)
Post * No College	-0.0644***	-0.0423***	-0.0210***	0.00564	0.00396	-0.225***	-0.0184	0.0218*
	(0.0217)	(0.0127)	(0.00537)	(0.0177)	(0.0166)	(0.0249)	(0.0222)	(0.0125)
Post * Veteran	0.118**	0.0646**	0.0387***	0.0500	0.0927**	0.0455	0.0839*	0.0509*
	(0.0534)	(0.0290)	(0.0137)	(0.0502)	(0.0457)	(0.0640)	(0.0507)	(0.0282)
Post * Median HHI	0.00551	-0.00314	0.00300	-0.0190*	0.00599	-0.00805	0.0205*	-0.0151**
	(0.0118)	(0.00700)	(0.00276)	(0.0111)	(0.0106)	(0.0116)	(0.0110)	(0.00708)
Observations	4,660	4,660	4,660	4,660	4,660	4,660	4,660	4,660
R^2	0.639	0.714	0.693	0.320	0.610	0.883	0.499	0.525

(b) Non-white

	MDI Index			Dimensions				
	MDI	A	A*MDI	Disability	NoInsurance	NoHighschool	Poverty	Unemployment
Post * NTR Gap	0.527***	0.296***	0.177**	0.332**	0.193	0.0727	0.474***	0.409***
	(0.194)	(0.0892)	(0.0865)	(0.137)	(0.183)	(0.146)	(0.167)	(0.120)
NTR rate	-5.387	-1.525	-2.813*	1.238	-4.739*	-1.604	-2.877	0.358
	(3.883)	(1.855)	(1.572)	(2.164)	(2.509)	(2.902)	(3.473)	(2.507)
MFA rate	-8,145*	-4,358**	-3,574**	-6,239	-4,055	-1,210	-2,406	-7,878**
	(4,475)	(2,047)	(1,745)	(3,920)	(4,984)	(5,455)	(3,916)	(3,119)
Post * No College	0.0255	0.0231	-0.00768	0.0197	0.0477	-0.113*	0.0959	0.0648
	(0.0676)	(0.0308)	(0.0292)	(0.0492)	(0.0532)	(0.0634)	(0.0740)	(0.0441)
Post * Veteran	0.0912	0.0440	0.00652	0.0581	0.0785	0.00388	0.0646	0.0148
	(0.153)	(0.0764)	(0.0685)	(0.104)	(0.141)	(0.153)	(0.159)	(0.107)
Post * Median HHI	-0.0499	-0.0281**	-0.00976	-0.0417*	-0.0696**	-0.00134	0.0551*	-0.0828***
	(0.0318)	(0.0137)	(0.0138)	(0.0246)	(0.0274)	(0.0331)	(0.0299)	(0.0186)
Observations	4,524	4,524	4,524	4,524	4,524	4,524	4,524	4,524
R^2	0.219	0.266	0.209	0.152	0.130	0.487	0.177	0.188

Note. Standard errors clustered on MSAs in parentheses, MSA and year fixed effects.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 3.9: White results by age

(a) Age 17-24

	MDI Index			Dimensions				
	MDI	A	A*MDI	Disability	NoInsurance	NoHighschool	Poverty	Unemployment
Post * NTR Gap	0.220*	0.120**	0.0888**	0.0583	-0.0233	0.407***	0.0728	0.0845
	(0.129)	(0.0574)	(0.0398)	(0.0376)	(0.126)	(0.148)	(0.0960)	(0.0689)
NTR rate	-2.028	-1.039	-0.390	-0.0608	-3.745*	3.023	-3.200	-1.211
	(2.731)	(1.149)	(0.900)	(0.657)	(2.203)	(2.628)	(2.350)	(1.225)
MFA rate	50.02	761.9	136.0	368.3	3,482	-3,938	5,448	-1,551
	(3,461)	(1,818)	(1,320)	(1,207)	(3,123)	(4,315)	(3,955)	(2,573)
Post * No College	0.0391	0.00732	0.00979	0.00932	-0.000210	-0.0442	0.0367	0.0351
	(0.0552)	(0.0242)	(0.0181)	(0.0203)	(0.0428)	(0.0642)	(0.0468)	(0.0335)
Post * Veteran	0.0213	-0.0202	-0.0273	-0.00185	0.113	-0.129	0.0384	-0.122
	(0.146)	(0.0679)	(0.0492)	(0.0411)	(0.129)	(0.153)	(0.114)	(0.0806)
Post * Median HHI	0.0573*	0.0227*	0.0228**	-0.00303	0.00847	0.0301	0.0557***	0.0222
	(0.0302)	(0.0134)	(0.00968)	(0.00854)	(0.0245)	(0.0303)	(0.0209)	(0.0185)
Observations	44,657	4,657	4,657	4,657	4,657	4,657	4,657	4,657
R^2	0.292	0.321	0.300	0.088	0.277	0.365	0.253	0.138

(b) Age 25-40

	MDI Index			Dimensions				
	MDI	A	A*MDI	Disability	NoInsurance	NoHighschool	Poverty	Unemployment
Post * NTR Gap	0.0907	0.0681*	0.0252	0.0877**	0.0548	-0.0909	0.0885	0.201***
	(0.0767)	(0.0391)	(0.0173)	(0.0376)	(0.0717)	(0.0638)	(0.0791)	(0.0450)
NTR rate	-1.389	-0.205	-0.198	0.524	-1.763	-0.527	-0.875	1.619**
	(1.340)	(0.701)	(0.338)	(0.809)	(1.327)	(1.517)	(1.219)	(0.772)
MFA rate	1,002	1,501	472.4	-1,277	5,490*	3,044	1,528	-1,282
	(3,286)	(1,771)	(1,023)	(1,516)	(2,903)	(2,812)	(3,415)	(1,359)
Post * No College	-0.0621*	-0.0422**	-0.0157**	0.0124	-0.00535	-0.241***	-0.00739	0.0309
	(0.0332)	(0.0183)	(0.00770)	(0.0143)	(0.0342)	(0.0317)	(0.0291)	(0.0187)
Post * Veteran	0.132	0.0912**	0.0452*	0.0713*	0.115	0.103	0.117*	0.0504
	(0.0867)	(0.0462)	(0.0234)	(0.0394)	(0.0958)	(0.0839)	(0.0684)	(0.0499)
Post * Median HHI	0.00674	0.00212	0.00233	-0.0177***	-0.00285	0.00182	0.0337**	-0.00435
	(0.0161)	(0.00954)	(0.00366)	(0.00656)	(0.0210)	(0.0152)	(0.0144)	(0.00933)
Observations	4,660	4,660	4,660	4,660	4,660	4,660	4,660	4,660
R^2	0.463	0.546	0.474	0.168	0.461	0.775	0.362	0.289

(c) Age 41-55

	MDI Index			Dimensions				
	MDI	A	A*MDI	Disability	NoInsurance	NoHighschool	Poverty	Unemployment
Post * NTR Gap	0.100	0.0126	0.0149	0.0243	0.0746	-0.250***	0.114*	0.0995
	(0.0772)	(0.0429)	(0.0172)	(0.0548)	(0.0701)	(0.0623)	(0.0646)	(0.0607)
NTR rate	0.425	0.146	-0.0475	-0.239	0.925	-0.0127	-0.253	0.311
	(1.233)	(0.747)	(0.325)	(1.149)	(1.274)	(1.403)	(1.043)	(0.980)
MFA rate	4,022	2,627*	1,398*	2,956	5,758***	1,772	712.9	1,938
	(3,206)	(1,574)	(823.2)	(1,941)	(2,207)	(2,420)	(2,403)	(2,759)
Post * No College	-0.0618**	-0.0354**	-0.0154**	-0.000270	0.0245	-0.202***	-0.0193	0.0201
	(0.0303)	(0.0144)	(0.00702)	(0.0248)	(0.0247)	(0.0286)	(0.0226)	(0.0189)
Post * Veteran	0.152**	0.0928**	0.0508***	0.0966	0.0953	0.117	0.0337	0.121**
	(0.0745)	(0.0411)	(0.0180)	(0.0633)	(0.0667)	(0.0823)	(0.0554)	(0.0487)
Post * Median HHI	-0.00490	-0.00448	0.000533	-0.00994	0.0111	0.00697	-0.0101	-0.0205*
	(0.0159)	(0.00772)	(0.00360)	(0.0134)	(0.0132)	(0.0132)	(0.0101)	(0.0107)
Observations	4,659	4,659	4,659	4,659	4,659	4,659	4,659	4,659
R^2	0.447	0.537	0.481	0.180	0.416	0.784	0.328	0.368

(d) Age over 56

	MDI Index			Dimensions				
	MDI	A	A*MDI	Disability	NoInsurance	NoHighschool	Poverty	Unemployment
Post * NTR Gap	0.166*	0.0488	0.0386	0.157	0.0449	-0.0963	0.00161	0.137***
	(0.0868)	(0.0445)	(0.0241)	(0.126)	(0.0563)	(0.1000)	(0.0515)	(0.0506)
NTR rate	3.339**	1.584*	0.943**	3.412*	1.321*	1.622	0.127	1.438
	(1.525)	(0.804)	(0.443)	(2.016)	(0.796)	(1.616)	(1.000)	(0.882)
MFA rate	-3,041	-1,382	-1,088*	-3,572	602.0	-2,914	-1,520	492.8
	(1,970)	(1,091)	(622.2)	(3,139)	(1,308)	(3,254)	(1,637)	(1,880)
Post * No College	-0.0978**	-0.0540**	-0.0407***	0.0372	0.0114	-0.274***	-0.0510**	0.00605
	(0.0410)	(0.0222)	(0.0114)	(0.0525)	(0.0229)	(0.0533)	(0.0247)	(0.0177)
Post * Veteran	0.136	0.0564	0.0517**	0.110	-0.0113	0.0771	0.0529	0.0534
	(0.0907)	(0.0483)	(0.0260)	(0.123)	(0.0412)	(0.116)	(0.0585)	(0.0443)
Post * Median HHI	0.00183	-0.0135	0.00312	-0.00800	0.0103	-0.0440*	0.00129	-0.0272***
	(0.0239)	(0.0131)	(0.00708)	(0.0337)	(0.00916)	(0.0257)	(0.0119)	(0.00939)
Observations	4,660	4,660	4,660	4,660	4,660	4,660	4,660	4,660
R^2	0.447	0.581	0.515	0.223	0.269	0.806	0.255	0.368

Note. Standard errors clustered on MSAs in parentheses, MSA and year fixed effects.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 3.10: Non-white results by age

(a) Age 17-24

	MDI Index			Dimensions				
	MDI	A	A*MDI	Disability	NoInsurance	NoHighschool	Poverty	Unemployment
Post * NTR Gap	0.487*	0.244**	0.199	0.0544	0.131	0.209	0.587**	0.237*
	(0.254)	(0.106)	(0.123)	(0.104)	(0.257)	(0.314)	(0.276)	(0.130)
NTR rate	-7.709	-3.163	-3.247	-0.209	-7.532**	-9.666	-1.466	3.058
	(5.116)	(2.401)	(2.361)	(1.676)	(3.724)	(6.117)	(6.411)	(3.738)
MFA rate	-12,896*	-6,261*	-6,804**	1,663	-12,526	-3,313	-6,560	-10,569*
	(7,621)	(3,491)	(3,065)	(3,464)	(8,050)	(9,894)	(7,723)	(5,516)
Post * No College	-0.131	-0.0253	-0.0559	-0.0239	0.105	-0.245*	0.124	-0.0864
	(0.113)	(0.0477)	(0.0540)	(0.0588)	(0.121)	(0.131)	(0.104)	(0.0688)
Post * Veteran	0.426	0.199*	0.196	0.132	0.272	0.0444	0.0903	0.454***
	(0.268)	(0.108)	(0.124)	(0.0894)	(0.261)	(0.254)	(0.266)	(0.165)
Post * Median HHI	-0.0263	-0.0243	-0.0105	-0.000967	0.0267	-0.132**	0.0835*	-0.0991***
	(0.0557)	(0.0214)	(0.0239)	(0.0252)	(0.0544)	(0.0514)	(0.0477)	(0.0312)
Observations	3,997	3,997	3,997	3,997	3,997	3,997	3,997	3,997
R^2	0.148	0.169	0.167	0.101	0.110	0.183	0.140	0.094

(b) Age 25-40

	MDI Index			Dimensions				
	MDI	A	A*MDI	Disability	NoInsurance	NoHighschool	Poverty	Unemployment
Post * NTR Gap	0.472**	0.284***	0.169*	0.160	0.247	-0.0748	0.547***	0.542***
	(0.212)	(0.102)	(0.0949)	(0.129)	(0.220)	(0.186)	(0.192)	(0.152)
NTR rate	-0.955	1.228	-0.765	1.376	-3.061	-0.559	5.412	2.972
	(4.971)	(2.293)	(1.927)	(1.812)	(4.041)	(3.286)	(3.826)	(4.324)
MFA rate	874.8	-729.7	-586.2	-4,476	1,797	2,715	5,617	-9,301*
	(5,177)	(2,867)	(2,032)	(3,120)	(5,907)	(6,215)	(4,832)	(4,750)
Post * No College	-0.00609	-0.0183	-0.00751	-0.0107	-0.0177	-0.146**	0.0519	0.0313
	(0.0903)	(0.0406)	(0.0382)	(0.0512)	(0.0852)	(0.0722)	(0.0940)	(0.0611)
Post * Veteran	0.0252	-0.0844	-0.0423	-0.0205	-0.0333	-0.0433	-0.0904	-0.235
	(0.190)	(0.0972)	(0.0869)	(0.127)	(0.191)	(0.176)	(0.218)	(0.155)
Post * Median HHI	-0.0336	-0.0311*	-0.00554	-0.0439**	-0.112***	-0.00405	0.0686	-0.0639*
	(0.0388)	(0.0172)	(0.0171)	(0.0213)	(0.0405)	(0.0331)	(0.0420)	(0.0328)
Observations	4,320	4,320	4,320	4,320	4,320	4,320	4,320	4,320
R^2	0.150	0.183	0.165	0.083	0.112	0.378	0.162	0.122

(c) Age 41-55

	MDI Index			Dimensions				
	MDI	A	A*MDI	Disability	NoInsurance	NoHighschool	Poverty	Unemployment
Post * NTR Gap	0.455**	0.297**	0.187*	0.445**	0.0424	-0.0105	0.541***	0.468**
	(0.218)	(0.120)	(0.0992)	(0.193)	(0.211)	(0.305)	(0.200)	(0.192)
NTR rate	-10.07**	-4.237	-5.908**	-2.219	-9.129**	-7.007	-3.618	0.789
	(5.041)	(2.688)	(2.300)	(3.209)	(4.322)	(4.550)	(4.388)	(3.131)
MFA rate	-16,888**	-7,770*	-8,570**	-12,138	-10,976*	-1,625	-14,303*	189.1
	(7,488)	(4,458)	(4,151)	(7,612)	(6,082)	(8,456)	(7,706)	(5,949)
Post * No College	0.173**	0.0354	0.0385	0.107	-0.0570	-0.0260	0.0425	0.110*
	(0.0849)	(0.0460)	(0.0397)	(0.0743)	(0.0894)	(0.114)	(0.0896)	(0.0660)
Post * Veteran	0.650***	0.275**	0.272**	0.0934	0.370	0.219	0.360*	0.332**
	(0.215)	(0.120)	(0.112)	(0.200)	(0.230)	(0.246)	(0.204)	(0.140)
Post * Median HHI	-0.0356	-0.0202	0.00431	-0.0326	-0.0675	0.0384	0.0262	-0.0652***
	(0.0404)	(0.0203)	(0.0205)	(0.0364)	(0.0437)	(0.0568)	(0.0386)	(0.0249)
Observations	4,166	4,166	4,166	4,166	4,166	4,166	4,166	4,166
R^2	0.165	0.186	0.171	0.138	0.129	0.374	0.129	0.181

(d) Age over 56

	MDI Index			Dimensions				
	MDI	A	A*MDI	Disability	NoInsurance	NoHighschool	Poverty	Unemployment
Post * NTR Gap	0.330	0.218*	0.164	0.0499	0.0615	0.437	0.147	0.392*
	(0.275)	(0.130)	(0.137)	(0.299)	(0.164)	(0.294)	(0.256)	(0.207)
NTR rate	-1.386	0.151	-0.774	-0.379	1.632	5.531	-4.138	-1.890
	(6.136)	(2.721)	(3.296)	(5.436)	(2.947)	(5.307)	(4.962)	(3.815)
MFA rate	-5,998	-2,904	-3,753	-14,339**	11,827*	2,695	-5,768	-8,936
	(8,049)	(4,352)	(3,995)	(6,712)	(6,373)	(12,268)	(6,840)	(6,054)
Post * No College	-0.118	0.0186	-0.0280	0.0728	-0.0504	-0.0795	0.0360	0.114
	(0.138)	(0.0626)	(0.0717)	(0.115)	(0.0740)	(0.134)	(0.123)	(0.0785)
Post * Veteran	-0.0108	0.0321	0.00120	-0.0516	0.0904	0.341	-0.0547	-0.165
	(0.383)	(0.169)	(0.190)	(0.263)	(0.168)	(0.351)	(0.329)	(0.164)
Post * Median HHI	-0.0139	-0.00831	0.00729	0.0583	-0.0981***	-0.0212	0.0842	-0.0647**
	(0.0728)	(0.0307)	(0.0350)	(0.0653)	(0.0326)	(0.0755)	(0.0544)	(0.0323)
Observations	3,928	3,928	3,928	3,928	3,928	3,928	3,928	3,928
R^2	0.185	0.222	0.203	0.135	0.114	0.383	0.151	0.182

Note. Standard errors clustered on MSAs in parentheses, MSA and year fixed effects.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 3.9 and Table 3.10 report results on race by age groups. For results on white people, we find the MDI indices are only significant for the younger adults of 17-24. While for nonwhites, MDI results are significant for ages 17-24, 25-40, and 41-55, with the coefficient estimates of approximately the same magnitude. In comparison, the younger adults' MDI estimates are larger for nonwhites. These results may indicate different channels of influence for the inter-generational effect for white and nonwhite households. In white households, being displaced from their original work for the parent generation may deliver a spillover effect to their children. While for nonwhite households, well-being deprivation may be the main channel of influence from parents to children.

Intra-household Dynamics

A critical question of our particular interest is whether the multidimensional deprivation patterns on young adults are inter-generational spillover effects from their parents, either being displaced from their original work or suffering from well-being deprivation? To that extent, we conduct regression on intra-household dynamics.

Our data allows us to do household-level analyses. Within the household, we can link young adults to their parents and know their parents' working status. Therefore, we can identify if parents' employment status affects young adults' well-being. Specifically, we restrict our sample to young adults aged 17-24 who live with their parents in the same household and identify their parents' working status as being employed or unemployed. Then we conduct difference-in-difference analysis using Equation 3.1.[12]

Results are reported in Table 3.11. Panel (a) and Panel (b) present results for young adults with their father and mother being unemployed, respectively. Regarding MDI indices, young adults with their father being unemployed are subject to significant well-being deprivation. The main driving forces are dimensions of highschool dropout and poverty. In comparison, we do not see any pattern for those whose mother is unemployed. While it

[12]In the ideal case, we can compare results between young adults who are living with their parents and those who are not. Our data limitation precludes us from making a comparison.

Table 3.11: Intra-household dynamics

(a) Father unemployed

	MDI Index			Dimensions				
	MDI	A	A*MDI	Disability	NoInsurance	NoHighschool	Poverty	Unemployment
Post * NTR Gap	1.303*	0.552*	0.722**	0.174	0.0151	1.419**	1.211**	-0.0603
	(0.717)	(0.317)	(0.348)	(0.248)	(0.577)	(0.659)	(0.614)	(0.536)
NTR rate	15.53	6.320	7.227	2.539	13.24	12.89	6.439	-3.509
	(11.48)	(4.679)	(5.614)	(4.400)	(11.42)	(10.53)	(9.378)	(10.90)
MFA rate	-52,725***	-13,846**	-24,740***	-4,427	-18,666	-7,738	-24,040*	-14,358
	(16,296)	(5,979)	(7,332)	(7,362)	(13,233)	(17,244)	(14,511)	(12,838)
Post * No College	0.0522	-0.0281	-0.0225	0.135*	0.346	-0.00949	-0.342*	-0.270
	(0.325)	(0.128)	(0.153)	(0.0787)	(0.304)	(0.328)	(0.204)	(0.232)
Post * Veteran	0.790	0.101	0.309	-0.209	0.255	0.250	0.166	0.0424
	(0.738)	(0.319)	(0.364)	(0.241)	(0.723)	(0.598)	(0.588)	(0.518)
Post * Median HHI	0.153	0.0894	0.0766	-0.00761	0.230*	0.257*	-0.0107	-0.0219
	(0.147)	(0.0563)	(0.0679)	(0.0436)	(0.126)	(0.131)	(0.118)	(0.111)
Observations	1,720	1,720	1,720	1,720	1,720	1,720	1,720	1,720
R^2	0.193	0.194	0.204	0.150	0.197	0.191	0.177	0.147

(b) Mother unemployed

	MDI Index			Dimensions				
	MDI	A	A*MDI	Disability	NoInsurance	NoHighschool	Poverty	Unemployment
Post * NTR Gap	-0.00614	0.202	-0.0238	0.365*	0.0272	-0.0370	-0.0522	0.709
	(0.705)	(0.295)	(0.330)	(0.205)	(0.702)	(0.722)	(0.552)	(0.520)
NTR rate	1.932	1.812	-1.812	6.926**	-9.008	4.933	-7.362	13.57
	(11.40)	(5.348)	(5.695)	(3.200)	(8.991)	(15.64)	(10.86)	(8.313)
MFA rate	-8,690	-3,570	-3,496	-3,289	-11,788	18,590	-7,545	-13,819
	(18,414)	(6,773)	(9,084)	(3,607)	(15,337)	(21,286)	(16,592)	(12,810)
Post * No College	-0.164	0.0563	-0.00431	0.119	-0.0261	0.342	0.109	-0.263
	(0.297)	(0.115)	(0.147)	(0.129)	(0.275)	(0.281)	(0.215)	(0.238)
Post * Veteran	0.712	0.265	0.145	0.226	0.166	0.614	0.0982	0.222
	(0.647)	(0.278)	(0.333)	(0.267)	(0.605)	(0.658)	(0.504)	(0.548)
Post * Median HHI	-0.0343	0.00557	0.0157	0.0394	-0.232*	0.217**	0.0930	-0.0894
	(0.120)	(0.0482)	(0.0591)	(0.0456)	(0.124)	(0.109)	(0.0904)	(0.120)
Observations	1,606	1,606	1,606	1,606	1,606	1,606	1,606	1,606
R^2	0.177	0.180	0.188	0.168	0.216	0.189	0.204	0.135

Note. Standard errors clustered on MSAs in parentheses, MSA and year fixed effects.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

is tricky to conclude that a parent's poor performance affects a 20-year-old who is already an independent individual, one potential mechanism may be that the 20-year old is still living with their parents and helping their parents financially or participating in household finances. If that is taking place, the inter-generational spillover effect could occur, especially when it comes to non-labor well-being parameters. Padilla-Walker, Son, and Nelson (2021) found the well-being status of parents impacts their children's life and well-being (anxiety, stress, loneliness, depression, and GPA). This finding is consistent with Family Systems Theory. Heinrich (2014) argued that parents' job loss presents a significant shock to the family subsystem - the stress associated with job loss can seriously undermine children's health and family relationships.

3.4.2 Difference-in-difference-in-difference results

In this section, as in Chapter 2, we explore the roles of higher minimum wage and welfare programs on MDI indices and dimensions. Table 3.12 reports estimates for μ_1 and μ_2 in Equation 3.3 for the MDI indices (columns 1-3) and dimensions (columns 4-8) for the whole sample population.

The coefficient estimates on minimum wage in Table 3.12 do not show significant patterns concerning deprivation indices and dimensions. As Dhongde and Haveman (2017) found, there was not much overlap between individuals who were income poor and those who were multidimensionally deprived. Almost 30% of individuals with income slightly above the poverty threshold experienced multiple deprivations. Specifically, triple-difference results by age group show a similar pattern - there is no significant result on people aged 17-24, as reported in Table 3.13. Young people typically constitute the minimum wage-bounded workforce, while higher minimum wage may not help with their multidimensional deprivation status. Two reasons might back up this pattern. First, a higher minimum wage may necessarily increase the income level of minimum wage-bounded workers. At the same time, it may only account for a single dimension for MDI indices which also contain

Table 3.12: Triple-difference: baseline results

	MDI Index			Dimensions				
	MDI	A	A*MDI	Disability	NoInsurance	NoHighschool	Poverty	Unemployment
Post * NTR Gap * MinWage	0.0431	-0.00286	0.0103	-0.102	0.00147	-0.231	0.147	0.170*
	(0.152)	(0.0774)	(0.0401)	(0.119)	(0.163)	(0.156)	(0.124)	(0.0961)
Post * NTR Gap * SWspending	0.0223	0.0157	-0.0113	0.148	-0.0856	0.266*	-0.121	-0.129
	(0.206)	(0.101)	(0.0479)	(0.173)	(0.163)	(0.151)	(0.142)	(0.121)
Post * NTR Gap	0.135	0.116	0.0284	0.363	0.0567	0.533*	-0.187	-0.184
	(0.269)	(0.135)	(0.0692)	(0.241)	(0.301)	(0.287)	(0.208)	(0.172)
Post * Swspending	-0.00720	-0.00725	0.00159	-0.0196	0.00227	-0.0637***	0.0198	0.0250
	(0.0297)	(0.0142)	(0.00690)	(0.0273)	(0.0242)	(0.0214)	(0.0201)	(0.0175)
Post * MinWage	-0.0309	-0.00899	-0.00754	-0.00113	-0.00628	0.0367	-0.0332	-0.0410**
	(0.0273)	(0.0138)	(0.00721)	(0.0207)	(0.0280)	(0.0266)	(0.0206)	(0.0164)
NTR rate	0.233	0.393	0.106	1.174	-0.485	0.538	-0.582	1.319*
	(1.153)	(0.593)	(0.331)	(0.846)	(0.941)	(1.006)	(0.919)	(0.714)
MFA rate	-1,265	-51.83	-388.8	-2,141	3,235**	-606.2	71.13	-817.9
	(1,561)	(776.0)	(418.3)	(1,380)	(1,258)	(1,000)	(1,432)	(1,198)
Post * No College	-0.0631***	-0.0403***	-0.0224***	0.00105	0.00679	-0.215***	-0.0173	0.0226*
	(0.0216)	(0.0116)	(0.00592)	(0.0178)	(0.0165)	(0.0236)	(0.0240)	(0.0134)
Post * Veteran	0.151***	0.0764***	0.0506***	0.0510	0.0975**	0.0593	0.116**	0.0581**
	(0.0563)	(0.0281)	(0.0157)	(0.0473)	(0.0465)	(0.0599)	(0.0482)	(0.0290)
Post * Median HHI	0.00305	-0.00348	0.00279	-0.0199*	0.000566	-0.00247	0.0274**	-0.0229***
	(0.0107)	(0.00587)	(0.00273)	(0.0110)	(0.00981)	(0.0106)	(0.0107)	(0.00722)
Observations	4,660	4,660	4,660	4,660	4,660	4,660	4,660	4,660
R^2	0.651	0.725	0.691	0.357	0.621	0.895	0.492	0.574

Note. Standard errors clustered on MSAs in parentheses, MSA and year fixed effects.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

information on insurance, education, disability, and poverty status. Second, the deprivation level of the young adults may be delivered from their parents' employment status, which we found earlier. Raising the minimum wage for young adults may not necessarily affect their well-being.[13]

[13] We notice that coefficient estimates of social welfare spending are not significant. It is expected that the general social safety net, such as unemployment insurance and welfare programs, may help those who are multidimnesionally deprived. However, the variable "social welfare spending" we used here includes many other factors such as cash assistance, Medicaid, and non-health social services. This variable may bring too much noise to the estimation and cannot be used to inform policy. We use this variable to control for other confounding characteristics from finding an effect on minimum wage.

Table 3.13: Triple-difference: age results

(a) Age 17-24

	MDI Index			Dimensions				
	MDI	A	A*MDI	Disability	NoInsurance	NoHighschool	Poverty	Unemployment
Post * NTR Gap * MinWage	0.177	0.0489	0.0650	0.105	-0.146	-0.138	0.207	0.217
	(0.341)	(0.150)	(0.113)	(0.103)	(0.332)	(0.318)	(0.362)	(0.203)
Post * NTR Gap * SWspending	-0.156	-0.136	-0.112	-0.0151	-0.475	0.266	-0.265	-0.190
	(0.438)	(0.182)	(0.133)	(0.111)	(0.340)	(0.349)	(0.342)	(0.164)
Post * NTR Gap	-0.0281	0.0423	-0.0386	-0.115	0.114	0.782	-0.251	-0.319
	(0.664)	(0.291)	(0.221)	(0.194)	(0.624)	(0.596)	(0.685)	(0.371)
Post * Swspending	0.0176	0.0208	0.0166	0.000749	0.0568	-0.0244	0.0499	0.0211
	(0.0655)	(0.0277)	(0.0199)	(0.0166)	(0.0535)	(0.0553)	(0.0489)	(0.0270)
Post * MinWage	-0.145**	-0.0639**	-0.0498**	-0.0221	-0.0456	-0.0924	-0.0992*	-0.0600*
	(0.0584)	(0.0258)	(0.0192)	(0.0196)	(0.0574)	(0.0652)	(0.0567)	(0.0361)
NTR rate	-1.195	-0.692	-0.338	0.442	-3.553	2.070	-2.262	-0.155
	(2.580)	(1.089)	(0.863)	(0.625)	(2.264)	(2.765)	(1.918)	(1.216)
MFA rate	-4,563	-1,503	-1,766	551.2	-1,745	-5,062	1,819	-3,079
	(3,089)	(1,534)	(1,074)	(1,076)	(2,986)	(4,147)	(2,955)	(2,763)
Post * No College	0.0147	-0.00146	0.000642	0.00166	0.0197	-0.0983*	0.0436	0.0260
	(0.0537)	(0.0217)	(0.0178)	(0.0188)	(0.0497)	(0.0594)	(0.0442)	(0.0317)
Post * Veteran	0.108	0.0364	0.0196	0.0177	0.175	-0.0390	0.0359	-0.00802
	(0.131)	(0.0576)	(0.0459)	(0.0363)	(0.126)	(0.139)	(0.0988)	(0.0716)
Post * Median HHI	0.0578*	0.0203	0.0216**	-0.00574	0.0162	0.0111	0.0715***	0.00830
	(0.0312)	(0.0124)	(0.0103)	(0.00954)	(0.0298)	(0.0285)	(0.0192)	(0.0172)
Observations	34,658	4,658	4,658	4,658	4,658	4,658	4,658	4,658
R^2	0.310	0.351	0.337	0.099	0.296	0.435	0.256	0.149

(b) Age 25-40

	MDI Index			Dimensions				
	MDI	A	A*MDI	Disability	NoInsurance	NoHighschool	Poverty	Unemployment
Post * NTR Gap * MinWage	0.0715	0.0875	0.0373	0.0479	-0.121	-0.111	0.364*	0.258*
	(0.217)	(0.113)	(0.0631)	(0.110)	(0.255)	(0.297)	(0.190)	(0.139)
Post * NTR Gap * SWspending	0.0976	0.0192	0.00331	0.135	0.227	9.40e-05	-0.153	-0.113
	(0.237)	(0.124)	(0.0564)	(0.120)	(0.290)	(0.188)	(0.221)	(0.191)
Post * NTR Gap	0.0678	-0.0414	-0.0191	0.0393	0.431	0.139	-0.559	-0.257
	(0.387)	(0.201)	(0.111)	(0.208)	(0.468)	(0.555)	(0.342)	(0.249)
Post * Swspending	-0.00899	-0.00150	0.000937	-0.00430	-0.0472	-0.00874	0.0300	0.0228
	(0.0350)	(0.0179)	(0.00830)	(0.0177)	(0.0438)	(0.0250)	(0.0320)	(0.0270)
Post * MinWage	-0.0179	-0.0166	-0.00334	-0.00329	0.0174	0.0266	-0.0735**	-0.0504**
	(0.0380)	(0.0195)	(0.0105)	(0.0196)	(0.0437)	(0.0452)	(0.0327)	(0.0222)
NTR rate	-1.136	0.164	-0.0502	0.459	-1.399	-0.443	0.0593	2.145**
	(1.599)	(0.846)	(0.438)	(0.742)	(1.244)	(1.719)	(1.352)	(0.893)
MFA rate	232.4	1,013	376.5	-1,056	4,763*	1,411	1,475	-1,526
	(3,051)	(1,597)	(950.0)	(1,287)	(2,819)	(2,539)	(2,769)	(1,365)
Post * No College	-0.0533	-0.0374**	-0.0142	0.00473	0.00764	-0.223***	-0.000428	0.0236
	(0.0335)	(0.0173)	(0.00891)	(0.0147)	(0.0279)	(0.0297)	(0.0357)	(0.0207)
Post * Veteran	0.155*	0.0960**	0.0446*	0.0678*	0.120	0.130	0.165** -	0.00304
	(0.0848)	(0.0431)	(0.0233)	(0.0386)	(0.0828)	(0.0843)	(0.0727)	(0.0467)
Post * Median HHI	-0.00334	-0.00427	0.000471	-0.0264***	-0.0137	-0.00665	0.0404**	-0.0150
	(0.0158)	(0.00855)	(0.00390)	(0.00726)	(0.0157)	(0.0149)	(0.0160)	(0.0105)
Observations	4,660	4,660	4,660	4,660	4,660	4,660	4,660	4,660
R^2	0.471	0.553	0.487	0.177	0.481	0.792	0.364	0.313

(c) Age 41-55

	MDI Index			Dimensions				
	MDI	A	A*MDI	Disability	NoInsurance	NoHighschool	Poverty	Unemployment
Post * NTR Gap * MinWage	0.315	0.169	0.0759	0.390**	-0.0223	-0.119	0.276	0.318**
	(0.216)	(0.117)	(0.0542)	(0.164)	(0.202)	(0.184)	(0.180)	(0.152)
Post * NTR Gap * SWspending	-0.0325	-0.0436	-0.00114	0.0582	-0.188	0.0982	-0.223	0.0368
	(0.235)	(0.127)	(0.0548)	(0.190)	(0.218)	(0.218)	(0.153)	(0.177)
Post * NTR Gap	-0.410	-0.254	-0.107	-0.616**	0.0835	0.0960	-0.411	-0.425
	(0.381)	(0.215)	(0.0952)	(0.284)	(0.360)	(0.353)	(0.342)	(0.268)
Post * Swspending	-0.00446	-0.00308	-0.00287	-0.00404	0.00709	-0.0554*	0.0259	0.0110
	(0.0323)	(0.0177)	(0.00778)	(0.0271)	(0.0314)	(0.0329)	(0.0214)	(0.0265)
Post * MinWage	-0.0441	-0.0113	-0.0103	-0.0662**	0.00983	0.0953***	-0.0407	-0.0545*
	(0.0381)	(0.0212)	(0.0106)	(0.0278)	(0.0362)	(0.0350)	(0.0298)	(0.0277)
NTR rate	0.0533	0.290	-0.163	0.194	0.585	-0.433	0.0527	1.052
	(1.435)	(0.843)	(0.413)	(1.179)	(1.303)	(1.490)	(1.023)	(1.142)
MFA rate	613.0	1,114	529.0	596.1	5,211**	2,122	-2,034	-326.0
	(2,497)	(1,277)	(657.4)	(1,804)	(2,388)	(2,605)	(1,371)	(1,870)
Post * No College	-0.0380	-0.0225	-0.0103	0.0101	0.0190	-0.165***	-0.00528	0.0286
	(0.0316)	(0.0145)	(0.00848)	(0.0235)	(0.0275)	(0.0296)	(0.0248)	(0.0211)
Post * Veteran	0.157**	0.0946**	0.0499**	0.0922	0.109	0.0958	0.0296	0.147***
	(0.0762)	(0.0391)	(0.0214)	(0.0576)	(0.0658)	(0.0762)	(0.0552)	(0.0503)
Post * Median HHI	-0.00469	-0.00295	0.00246	-0.0142	0.0161	0.0181	-0.00181	-0.0330***
	(0.0169)	(0.00764)	(0.00427)	(0.0128)	(0.0127)	(0.0147)	(0.0111)	(0.0111)
Observations	4,660	4,660	4,660	4,660	4,660	4,660	4,660	4,660
R^2	0.460	0.551	0.481	0.206	0.441	0.806	0.333	0.428

(d) Age over 56

	MDI Index			Dimensions				
	MDI	A	A*MDI	Disability	NoInsurance	NoHighschool	Poverty	Unemployment
Post * NTR Gap * MinWage	-0.429*	-0.300**	-0.110*	-0.465*	-0.0813	-0.564**	-0.193	-0.195
	(0.226)	(0.132)	(0.0582)	(0.272)	(0.185)	(0.283)	(0.159)	(0.182)
Post * NTR Gap * SWspending	0.148	0.139	0.0170	0.395	-0.0725	0.608**	-0.0572	-0.181
	(0.316)	(0.152)	(0.0800)	(0.430)	(0.109)	(0.295)	(0.144)	(0.136)
Post * NTR Gap	1.025**	0.673***	0.258**	1.148**	0.186	1.248**	0.359	0.422
	(0.449)	(0.246)	(0.110)	(0.546)	(0.349)	(0.524)	(0.264)	(0.338)
Post * Swspending	-0.0378	-0.0345	-0.00576	-0.0719	0.00554	-0.140***	0.00789	0.0262
	(0.0484)	(0.0230)	(0.0127)	(0.0694)	(0.0162)	(0.0416)	(0.0212)	(0.0203)
Post * MinWage	0.0681*	0.0473**	0.0203**	0.0370	0.0234	0.111**	0.0567**	0.00848
	(0.0353)	(0.0200)	(0.00915)	(0.0474)	(0.0287)	(0.0454)	(0.0274)	(0.0301)
NTR rate	2.586	1.323	0.789	2.779	1.290*	1.576	-0.380	1.350
	(1.658)	(0.828)	(0.505)	(2.174)	(0.760)	(1.612)	(1.074)	(0.944)
MFA rate	-2,672	-971.0	-1,171*	-4,056	1,224	-1,073	-1,031	80.37
	(1,843)	(1,055)	(632.4)	(2,880)	(1,245)	(3,076)	(1,665)	(1,641)
Post * No College	-0.0935**	-0.0502**	-0.0389***	0.0309	-0.00849	-0.233***	-0.0570**	0.0164
	(0.0383)	(0.0217)	(0.0122)	(0.0519)	(0.0204)	(0.0549)	(0.0234)	(0.0196)
Post * Veteran	0.143	0.0480	0.0642**	0.0792	-0.0267	0.0408	0.0995*	0.0471
	(0.0891)	(0.0456)	(0.0272)	(0.118)	(0.0418)	(0.108)	(0.0564)	(0.0489)
Post * Median HHI	0.00637	-0.00815	0.00489	0.00198	-0.00534	-0.0153	0.00429	-0.0264***
	(0.0239)	(0.0125)	(0.00779)	(0.0325)	(0.0104)	(0.0271)	(0.0117)	(0.00960)
Observations	4,660	4,660	4,660	4,660	4,660	4,660	4,660	4,660
R^2	0.477	0.600	0.526	0.246	0.279	0.823	0.279	0.439

Note. Standard errors clustered on MSAs in parentheses, MSA and year fixed effects.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

3.5 Robustness

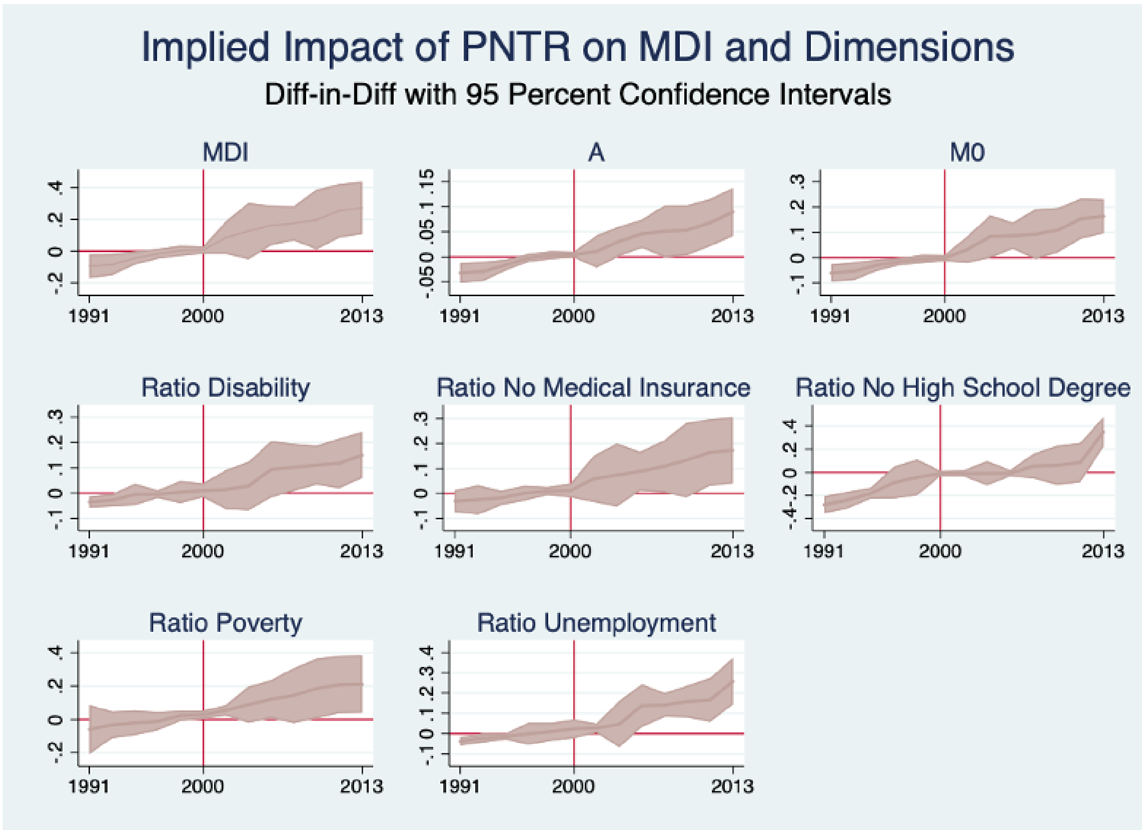
3.5.1 Timing of impacts

Our sample period includes the Great Recession of 2008, another considerable income shock to local economies. It would be hard to generalize our claims if our empirical results are driven by the coincidence of two large exogenous shocks. Hence, we separately estimate different time effects from the trade liberalization by running the following specification:

$$\begin{aligned} LHS_{mt} = (\theta_a \cdot \mathbf{1}_{01 \leq year \leq 07} + \theta_b \cdot \mathbf{1}_{08 \leq year \leq 10} + \theta_c \cdot \mathbf{1}_{11 \leq year \leq 13} \times NTRGap_m \\ +(\gamma_a \cdot \mathbf{1}_{01 \leq year \leq 07} + \gamma_b \cdot \mathbf{1}_{08 \leq year \leq 10} + \gamma_c \cdot \mathbf{1}_{11 \leq year \leq 13} \times \boldsymbol{Z}_m \\ +\beta \boldsymbol{X}_{mt} + \delta_m + \delta_t + \varepsilon_{mt} \end{aligned} \tag{3.5}$$

where $\mathbf{1}_{01 \leq year \leq 07}$ refers to an indicator variable for the pre-Great-Recession period, $\mathbf{1}_{08 \leq year \leq 10}$ is indicator for Great Recession years, and $\mathbf{1}_{11 \leq year \leq 13}$ refers to the post-Great-Recession period. Hence, the DID estimates on θ_a, θ_b, θ_c are of interest. LHS_{mt} refers to the dependent variables of MDI measure and dimensions.

Figure 3.2 presents a matrix of graphs for reviewing the results of the estimates visually from the difference-in-difference estimation in Equation 3.5. The graphs for three MDI measures are positioned on the first row, and five dimensions on the second and third row. Each figure plots the three-period coefficient estimates of θ_a, θ_b, and θ_c along the full sample year 1990-2013. The graphs also display the 95 percent confidence interval. If the results are not driven by other concurrent incidences during 1990-2013, graphs should present a pattern where there is no pre-trend before 2000, a significant jump/dive on the conferral of the PNTR in 2000, and a stable increase/decrease after 2000. As indicated in Figure 3.2, estimates in all graphs are statistically indistinguishable from zero before 2000, but take a spike around the time of the change in policy in 2000, and remain elevated through 2013. The graphs confirm that the robustness of the difference-in-difference regression results that PNTR increased multidimensional deprivation and that other concurrent incidences do not drive our findings in Section 3.4.



Note. Figures display the 95 percent confidence interval of the implied impact of an interquartile shift in a MSA's exposure to PNTR on crime rates using estimates from Equation 3.5 for three measures of MDI and each of five dimensions

Figure 3.2: Implied impact of PNTR on MDI and dimensions

3.5.2 Additional controls

To the extent that the differences in MDI impact are driven by the concentration of those demographics in certain regions, we include additional controls to account for the MSA-level demographics. Specifically, we control for the 1990 share of residents younger than 25 years old, the 1990 share of whites, the 1990 share of blacks, and the 1990 share of males.[14]

Table 3.14 report the results for the whole sample. In comparison to the baseline results in Table 3.3, it is clear that the significant patterns on MDI indices remain, and the main driving forces are dimensions of disability, no medical insurance coverage, poverty, and unemployment, consistent with the baseline results. In regards to the magnitude of the coefficient estimates, we find that the estimates are about the same level while the baseline results in Table 3.3 are slightly larger. Results in this section confirm that regional differences in demographics are negligible and they does not influence any of the significant patterns.

Table 3.14: Robustness: additional controls

	MDI Index			Dimensions				
	MDI	A	A*MDI	Disability	NoInsurance	NoHighschool	Poverty	Unemployment
Post * NTR Gap	0.174***	0.103***	0.0407**	0.128**	0.0845*	0.0208	0.0987**	0.184***
	(0.0655)	(0.0332)	(0.0157)	(0.0514)	(0.0484)	(0.0546)	(0.0476)	(0.0381)
NTR rate	-0.152	0.300	-0.0110	1.294	-0.719	0.946	-1.028	1.007
	(1.043)	(0.546)	(0.294)	(0.818)	(0.915)	(0.937)	(0.845)	(0.687)
MFA rate	-968.8	-71.72	-281.3	-1,888	2,997**	-720.3	162.4	-909.7
	(1,570)	(784.7)	(415.6)	(1,414)	(1,250)	(956.0)	(1,408)	(1,142)
Post * Age 25+	-0.0203	-0.0262	0.00817	0.0121	-0.0741	-0.123**	0.00861	0.0451
	(0.0534)	(0.0293)	(0.0144)	(0.0428)	(0.0631)	(0.0601)	(0.0519)	(0.0384)
Post * White	0.0797**	0.00519	0.0297***	0.0214	0.00154	-0.0610	0.0595**	0.00446
	(0.0349)	(0.0179)	(0.0102)	(0.0289)	(0.0289)	(0.0394)	(0.0298)	(0.0223)
Post * Black	0.110***	0.0272	0.0382***	0.0370	0.0329	-0.0594	0.0682**	0.0573**
	(0.0345)	(0.0187)	(0.0110)	(0.0333)	(0.0297)	(0.0421)	(0.0312)	(0.0239)
Post * Male	0.468*	0.0956	0.173**	0.108	-0.0146	0.373	0.0608	-0.0497
	(0.280)	(0.147)	(0.0677)	(0.253)	(0.252)	(0.250)	(0.243)	(0.195)
Post * No College	-0.0557**	-0.0388***	-0.0204***	0.00381	0.00535	-0.204***	-0.0185	0.0196
	(0.0231)	(0.0121)	(0.00566)	(0.0173)	(0.0173)	(0.0250)	(0.0242)	(0.0125)
Post * Veteran	0.123**	0.0842***	0.0353**	0.0423	0.127**	0.104	0.0951*	0.0520
	(0.0583)	(0.0309)	(0.0143)	(0.0480)	(0.0523)	(0.0638)	(0.0527)	(0.0332)
Post * Median HHI	0.00189	-0.00445	0.00226	-0.0214*	-0.000217	-0.000664	0.0260**	-0.0260***
	(0.0115)	(0.00631)	(0.00281)	(0.0112)	(0.0103)	(0.0109)	(0.0112)	(0.00698)
Observations	4,660	4,660	4,660	4,660	4,660	4,660	4,660	4,660
R^2	0.652	0.725	0.693	0.357	0.622	0.895	0.493	0.576

Note. Standard errors clustered on MSAs in parentheses, MSA and year fixed effects.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

3.6 Conclusion

The increased import competition from China brought severe labor market disruptions in the US. While previous studies mainly focus on labor market outcomes, this research fills

[14] Data are from the 1990 Decennial Census.

the gap. It provides nuanced analyses that trade exposure may also impact people's well-being and deliver an inter-generational effect on the younger generation.

We employ the Multidimensional Deprivation Index (MDI) by Dhongde and Haveman (2017) and estimate MSA's multidimensional deprivation effect of PNTR on different age-, gender-, and race groups. Results show that PNTR does have a significant impact on the well-being of people who live in more exposed regions, with driving forces of disability payment, no medical insurance coverage, poverty, and unemployment. Young adults aged 17-24 are the most impacted population, and lack of highschool education is the main contributing factor. Overall, results on males and females are both significant and of similar magnitude. In regards to race, nonwhite people are subject to higher well-being deprivation. To better explore the possible inter-generational effects, we conduct an intra-household analysis for the young adults. Results suggest that the inter-generational spillover effects may exist. Parents' employment status may have a significant impact on their children's life. Additionally, estimates on higher minimum wage and social welfare expenditures are not significant, which shows that income poor individuals are not necessarily multidimensionally deprived at the same time.

Our results have broad policy implications. First, supporting young adults will benefit society. Young adults, during challenging times, may be struggling to find a path to employment, economic security, and well-being. Policies that are oriented towards helping young adults maintaining healthy, productive, and skillful are critical to the nation's workforce. Second, policies of multiple dimensions are crucial to help those who are multidimensionally deprived, including but not limited to insurance coverage, poverty alleviation, education programs, etc.

Appendices

APPENDIX A

SUPPLEMENTARY TABLES AND FIGURES FOR "DOES MINIMUM WAGE INCREASE OR REDUCE CRIME? EVIDENCE FROM A NEGATIVE INCOME SHOCK"

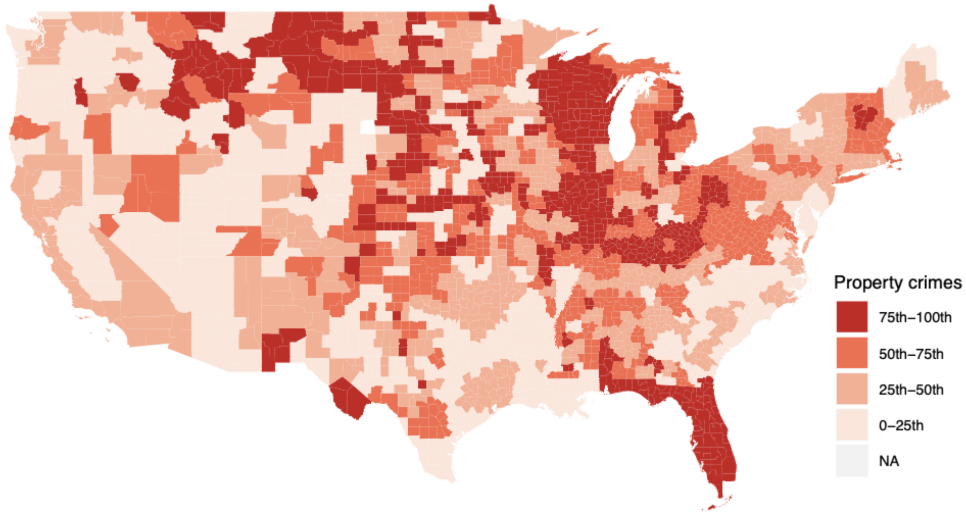
Table A.1: Commuting Zones with the highest and lowest NTR gaps

Commuting Zone	NTR Gap	Name of largest place in Commuting Zone
Highest		
1301	0.235	Bennettsville city, SC
1002	0.234	Morganton city, NC
602	0.234	Galax city, VA
1100	0.222	Hickory city, NC
8402	0.219	Washington city, GA
Lowest		
35905	0.009	Loa town, UT
34112	0.007	Bethel city, AK
27605	0.006	Rosebud CDP, SD
27604	0.005	Murdo city, SD
34105	0.004	Kotzebue city, AK

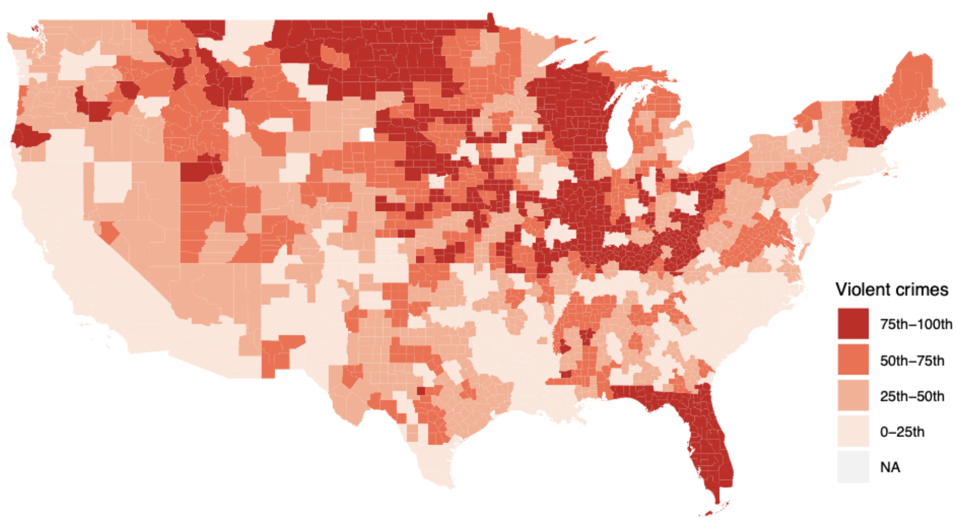
Table A.2: Unit cost of crime in the United States, 2010

	Unit Cost ($)
Property Crime	271,412
Burglary	5,159
Theft	1,982
Motor Vehicle Theft	8,874
Arson	11,126
Violent Crime	5,593,315
Murder	5,320,000
Rape	149,625
Robbery	38,903
Aggravated Assault	84,788

Note. Estimates according to Chalfin, 2015 and Heeks et al., 2018. Table reports the unit cost of index crimes in the United States in 2010 given the number of Uniform Crime Reports.

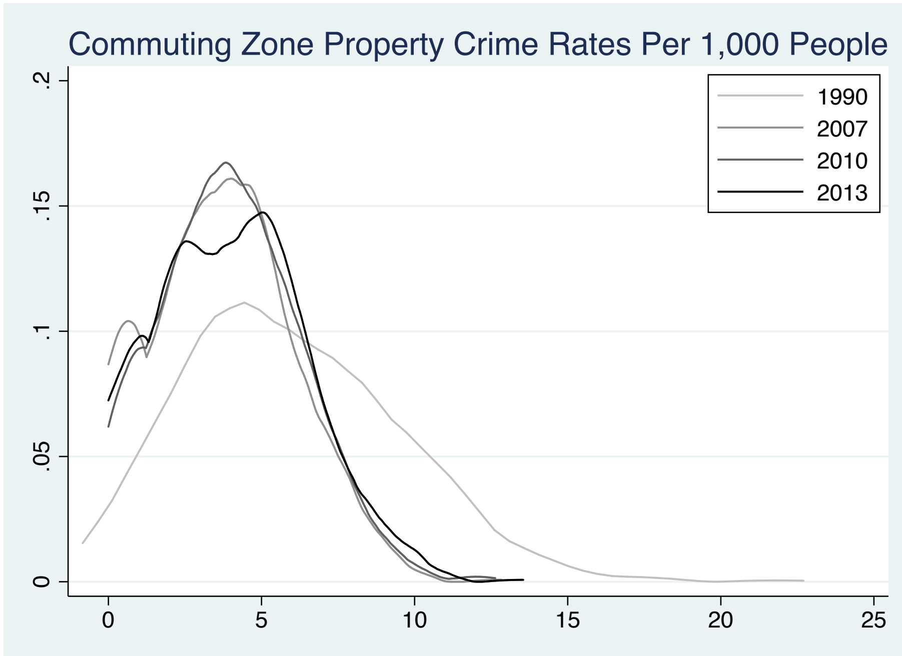


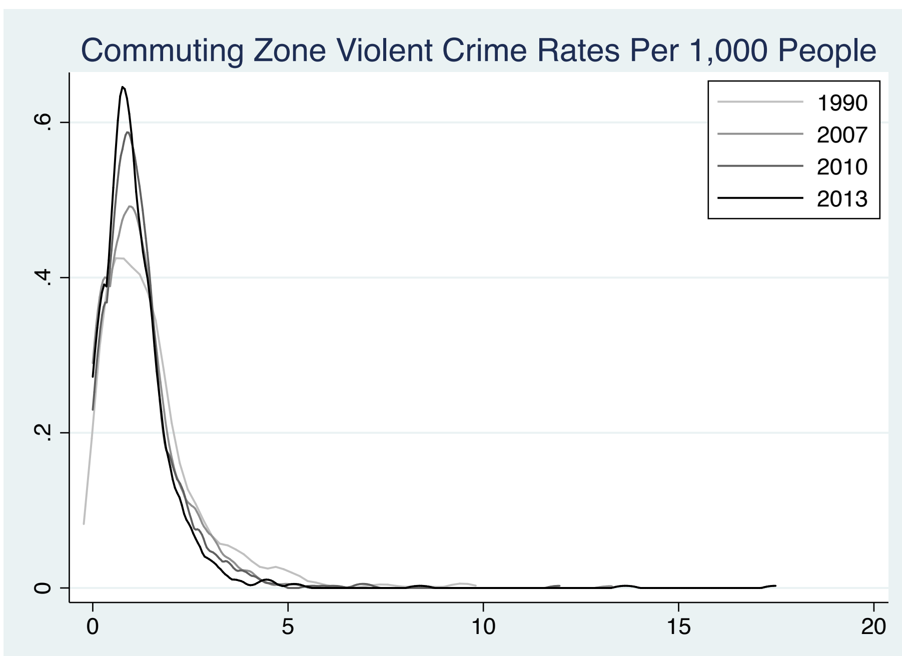
The mean of Property crime per 1,000 resident is 3.90 and its standard deviation is 2.57 (Q1=1.92, Q2=3.83, Q3=5.62).



For violent crime, the mean is 1.25 and the standard deviation is 1.42 (Q1=0.43, Q2=1.04, Q3=1.68).

Figure A.1: Number of arrests per 1,000 residents by Commuting Zone in 2000





Note. The number of Commuting Zones is 741. Statistics are generated from the 1990-2013 Uniform Crime Reports (UCR).

Figure A.2: Distribution of overall crime rates

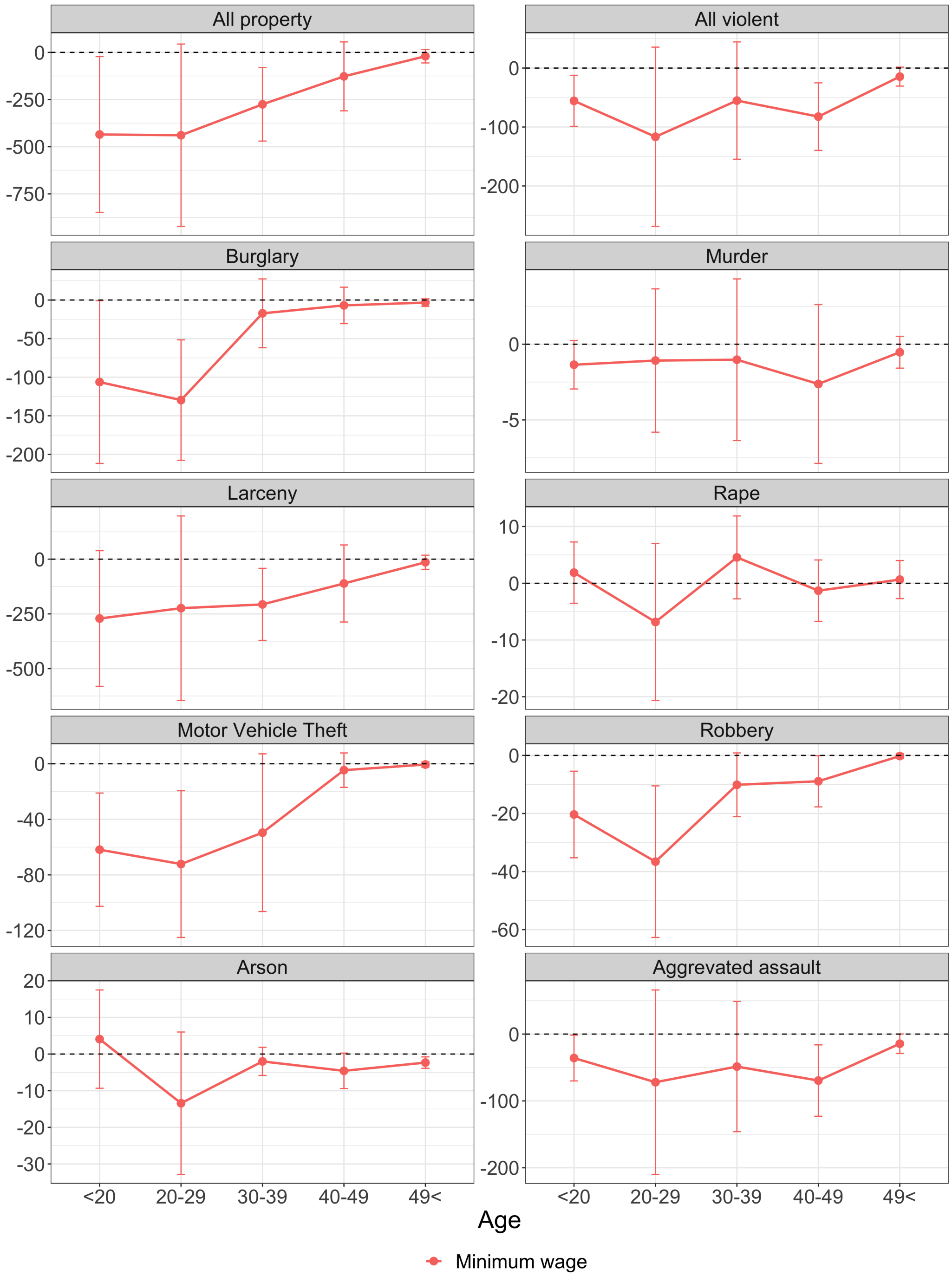


Figure A.3: Diff-Diff-Diff coefficients and 95% CI for age group

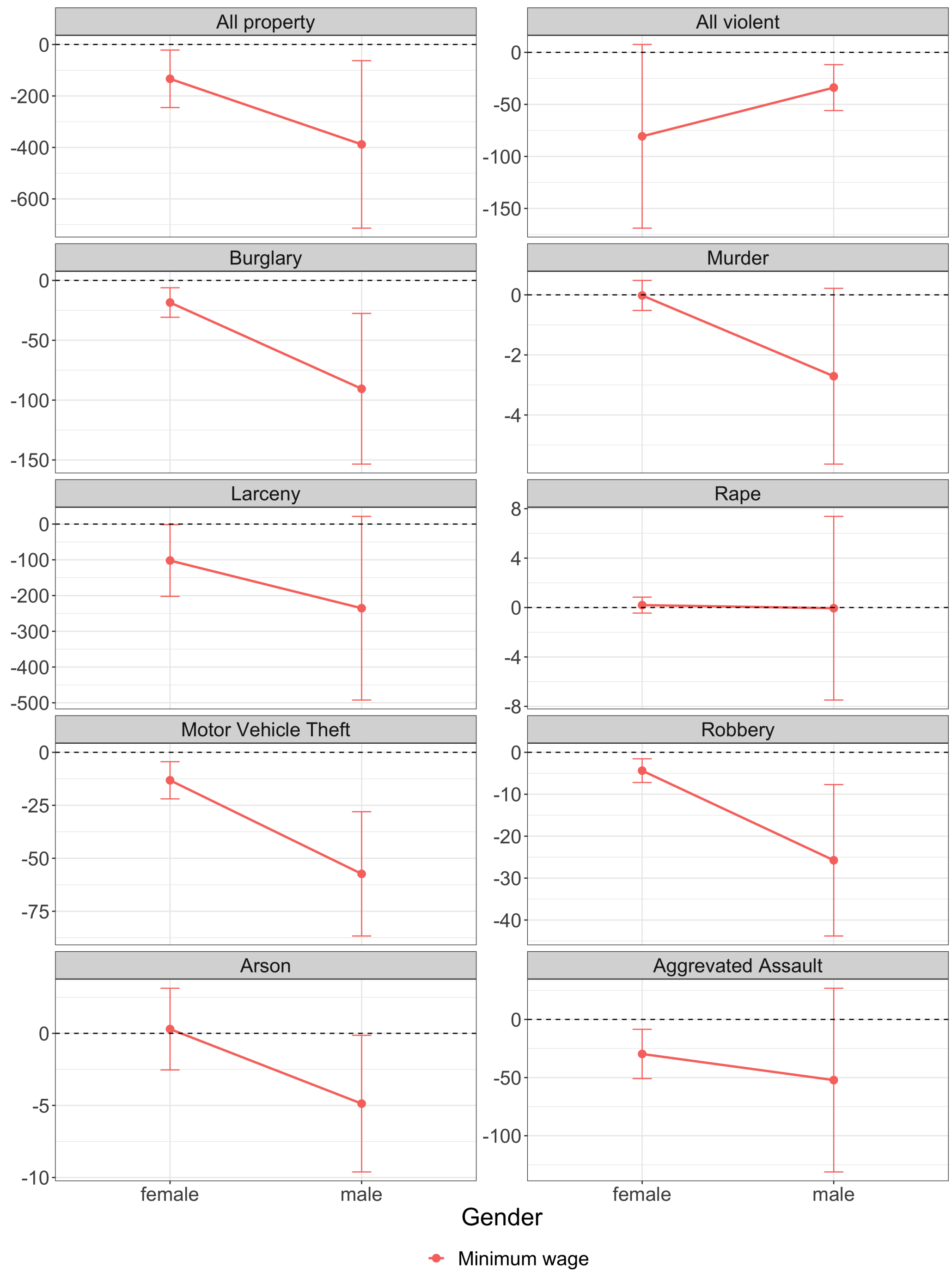


Figure A.4: Diff-Diff-Diff coefficients and 95% CI for gender

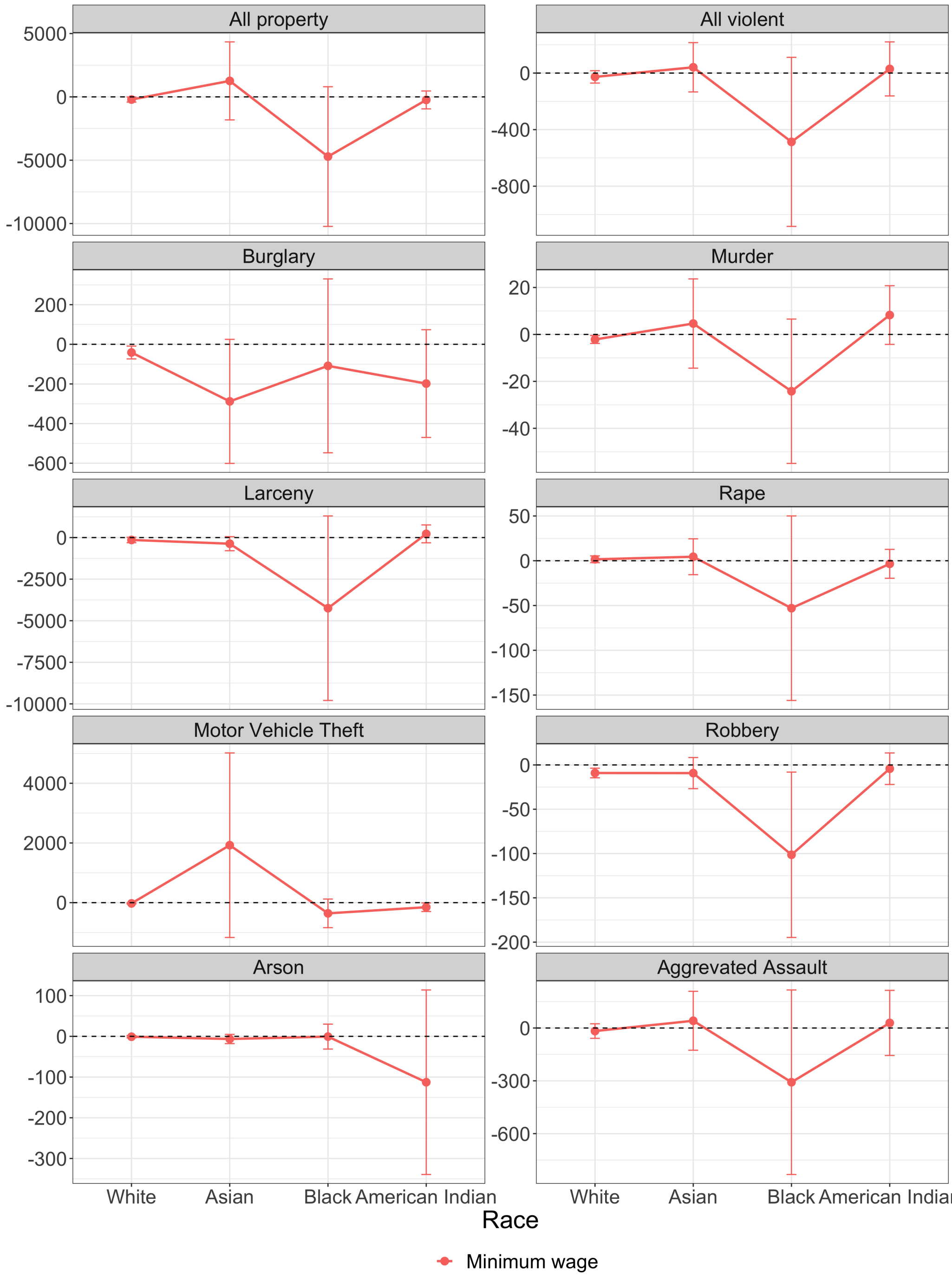
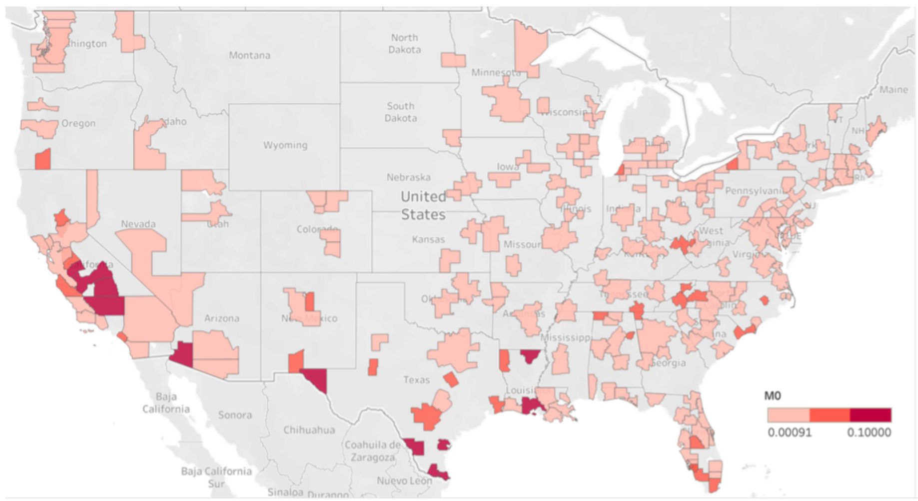


Figure A.5: Diff-Diff-Diff coefficients and 95% CI for race

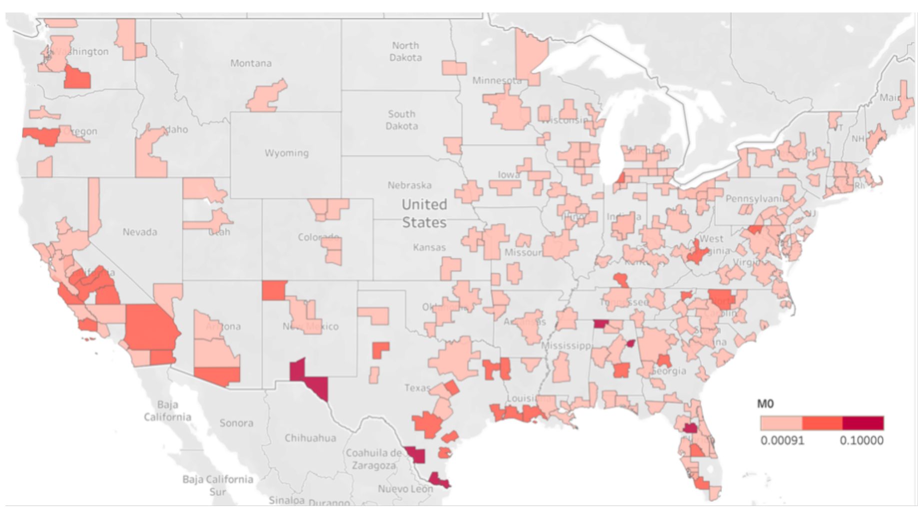
APPENDIX B

SUPPLEMENTARY TABLES AND FIGURES FOR "MULTIDIMENSIONAL IMPACTS OF TRADE LIBERALIZATION ON YOUNG ADULTS"



Note. Statistics used in this figure are from MDI_3^m

Figure B.1: MDI distribution in MSA, 2001



Note. Statistics used in this figure are from MDI_3^m

Figure B.2: MDI distribution in MSA, 2007

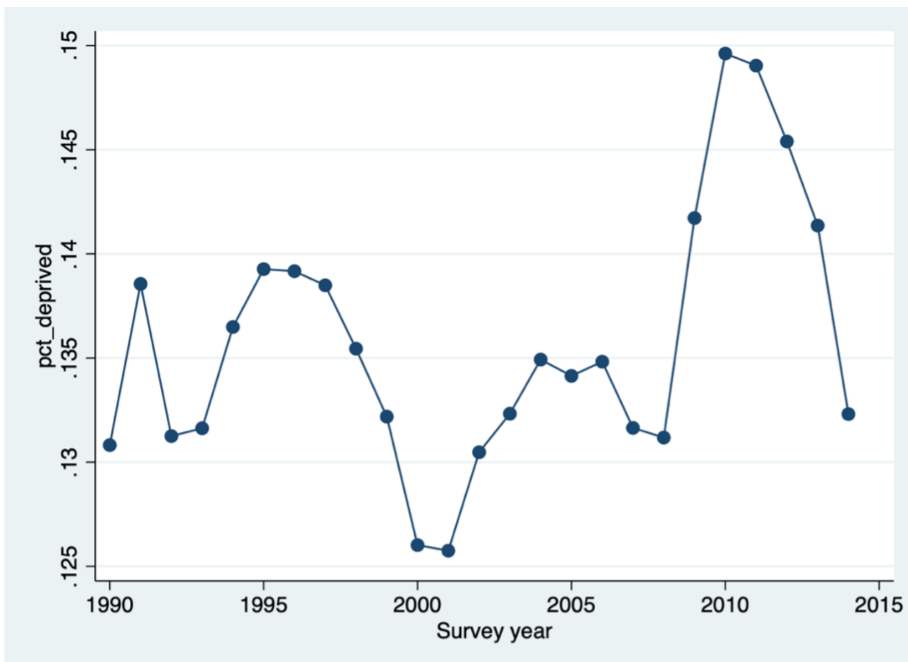


Figure B.3: Percent of individuals deprived in ≥ 2 dimensions

REFERENCES

Aduke, F. et al. (2012). "University education and poverty alleviation as mechanisms for enhancing youth development in Nigeria". In: *International Journal of Psychology and Counselling* 4.1, pp. 1–5.

Agan, A. Y. and M. D. Makowsky (2018). *The minimum wage, eitc, and criminal recidivism*. Tech. rep. National Bureau of Economic Research.

Aguayo-Tellez, E., J. Airola, C. Juhn, and C. Villegas-Sanchez (2014). *Did trade liberalization help women? The case of Mexico in the 1990s*. Emerald Group Publishing Limited.

Ajimotokin, S., A. Haskins, and Z. Wade (2015). "The Effects of Unemployment on Crime Rates in the US". In:

Alkire, S. and J. Foster (2011). "Counting and multidimensional poverty measurement". In: *Journal of public economics* 95.7-8, pp. 476–487.

Allan, E. A. and D. J. Steffensmeier (1989). "Youth, underemployment, and property crime: Differential effects of job availability and job quality on juvenile and young adult arrest rates". In: *American sociological review*, pp. 107–123.

Anderson, D. M. (2014). "In school and out of trouble? The minimum dropout age and juvenile crime". In: *Review of Economics and Statistics* 96.2, pp. 318–331.

Artuç, E., S. Chaudhuri, and J. McLaren (2010). "Trade shocks and labor adjustment: A structural empirical approach". In: *American economic review* 100.3, pp. 1008–45.

Autor, D. H., D. Dorn, and Hanson (2013). "The China syndrome: Local labor market effects of import competition in the United States". In: *American Economic Review* 103.6, pp. 2121–68.

Autor, D. H., D. Dorn, and Hanson (2015). "Untangling trade and technology: Evidence from local labour markets". In: *The Economic Journal* 125.584, pp. 621–646.

Autor, D. H., D. Dorn, and Hanson (2016). "The China shock: Learning from labor-market adjustment to large changes in trade". In: *Annual Review of Economics* 8, pp. 205–240.

Beauchamp, A. and S. Chan (2012). "Crime and the Minimum Wage". In: *Bc. edu*.

Beauchamp, A. and S. Chan (2014). "The minimum wage and crime". In: *The BE Journal of Economic Analysis & Policy* 14.3, pp. 1213–1235.

Becker, G. S. (1968). *Crime and punishment: An economic approach*. London: Palgrave Macmillan.

Benguria, F. and J. Ederington (2017). "Decomposing the effect of trade on the gender wage gap". In: *Available at SSRN 2907094*.

Bertrand, M., E. Duflo, and S. Mullainathan (2004). "How much should we trust differences-in-differences estimates?" In: *The Quarterly journal of economics* 119.1, pp. 249–275.

Besedeš, T., S. H. Lee, and Yang (2021). "Trade liberalization and gender gaps in local labor market outcomes: Dimensions of adjustment in the United States". In: *Journal of Economic Behavior & Organization* 183, pp. 574–588.

Black and Brainerd (2004). "Importing equality? The impact of globalization on gender discrimination". In: *ILR Review* 57.4, pp. 540–559.

Black, D. and Sanders (2002). "The impact of economic conditions on participation in disability programs: Evidence from the coal boom and bust". In: *American Economic Review* 92.1, pp. 27–50.

Boadway, R. and K. Cuff (2001). "A minimum wage can be welfare-improving and employment-enhancing". In: *European Economic Review* 45.3, pp. 553–576.

Bøler, E. A., B. Javorcik, and K. H. Ulltveit-Moe (2018). "Working across time zones: Exporters and the gender wage gap". In: *Journal of International Economics* 111, pp. 122–133.

Brussevich, M. (2018). "Does trade liberalization narrow the gender wage gap? The role of sectoral mobility". In: *European Economic Review* 109, pp. 305–333.

Byun, S. J. and S. H. Lee (2019). *China Shock, local credit supply, and the amplified impact on the U.S. labor market*. Working paper.

Caliendo, L., M. Dvorkin, and F. Parro (2019a). "Trade and Labor Market Dynamics: General Equilibrium Analysis of the China Trade Shock". In: *Econometrica* 87.3, pp. 741–835. eprint: https://onlinelibrary.wiley.com/doi/pdf/10.3982/ECTA13758.

Caliendo, L., M. Dvorkin, and F. Parro (2019b). "Trade and labor market dynamics: General equilibrium analysis of the china trade shock". In: *Econometrica* 87.3, pp. 741–835.

Chalfin, A. (2015). "Economic costs of crime". In: *The encyclopedia of crime and punishment*, pp. 1–12.

Chalfin, A. and J. McCrary (2018). “Are US cities underpoliced? Theory and evidence”. In: *Review of Economics and Statistics* 100.1, pp. 167–186.

Charles, K. K., E. Hurst, and M. Schwartz (2019). “The transformation of manufacturing and the decline in US employment”. In: *NBER Macroeconomics Annual* 33.1, pp. 307–372.

Chaudhry, I. S., S. Malik, A. Hassan, and M. Z. Faridi (2010). “Does education alleviate poverty? Empirical evidence from Pakistan”. In: *International Research Journal of Finance and Economics* 52, pp. 134–141.

Che, Y., Xu, and Zhang (2018). “Chinese import competition, crime, and government transfers in us”. In: *Journal of Comparative Economics* 46.2, pp. 544–567.

Chioda, L., J. M. De Mello, and R. R. Soares (2016). “Spillovers from conditional cash transfer programs: Bolsa Famılia and crime in urban Brazil”. In: *Economics of Education Review* 54, pp. 306–320.

Corman, H. and N. Mocan (2005). “Carrots, sticks, and broken windows”. In: *The Journal of Law and Economics* 48.1, pp. 235–266.

Council, N. R. et al. (2015). “Investing in the health and well-being of young adults”. In:

Crutchfield, R. D. (2011). *Labor Force Participation, Labor Markets, and Crime*. DIANE Publishing.

Dachis, B., G. Duranton, and M. A. Turner (2012). “The effects of land transfer taxes on real estate markets: evidence from a natural experiment in Toronto”. In: *Journal of economic Geography* 12.2, pp. 327–354.

Danziger, S., G. Jakubson, S. Schwartz, and E. Smolensky (1982). “Work and welfare as determinants of female poverty and household headship”. In: *The Quarterly Journal of Economics* 97.3, pp. 519–534.

Dave, D., M. Deza, and B. P. Horn (2018). *Prescription drug monitoring programs, opioid abuse, and crime*. Tech. rep. National Bureau of Economic Research.

Department of Health and Human Services (July 2004). *Spending on Social Welfare Programs in Rich and Poor States*. Contract Number: 282-98-0016.

Devereux, S. (2002). “Can social safety nets reduce chronic poverty?” In: *Development Policy Review* 20.5, pp. 657–675.

Dhongde, S. and R. Haveman (2017). “Multi-dimensional deprivation in the US”. In: *Social Indicators Research* 133.2, pp. 477–500.

Dorn, D., Hanson, et al. (2019). “When work disappears: Manufacturing decline and the falling marriage market value of young men”. In: *American Economic Review: Insights* 1.2, pp. 161–78.

Ederington, J., J. Minier, and K. R. Troske (2009). “Where the Girls Are: Trade and labor market segregation in Colombia”. In:

Executive Office of the President (Oct. 2016). *Raising the Minimum Wage: A Progress Update?* Working Paper.

Feenstra, Xu, and Ma (2019). *Magnification of the ‘China Shock’ Through the U.S. Housing Market*. Working Paper 26432. National Bureau of Economic Research.

Feler, L. and M. Z. Senses (2017a). “Trade shocks and the provision of local public goods”. In: *American Economic Journal: Economic Policy* 9.4, pp. 101–43.

Feler, L. and M. Z. Senses (Nov. 2017b). “Trade Shocks and the Provision of Local Public Goods”. In: *American Economic Journal: Economic Policy* 9.4, pp. 101–43.

Fender, J. (1999). “A general equilibrium model of crime and punishment”. In: *Journal of Economic Behavior & Organization* 39.4, pp. 437–453.

Fergusson, D., N. Swain-Campbell, and J. Horwood (2004). “How does childhood economic disadvantage lead to crime?” In: *Journal of child psychology and psychiatry* 45.5, pp. 956–966.

Fishback, P. V., R. S. Johnson, and S. Kantor (2010). “Striking at the roots of crime: The impact of welfare spending on crime during the great depression”. In: *The Journal of Law and Economics* 53.4, pp. 715–740.

Flanagan, C. A. and J. S. Eccles (1993). “Changes in parents’ work status and adolescents’ adjustment at school”. In: *Child development* 64.1, pp. 246–257.

Fone, Z. S., J. J. Sabia, and R. Cesur (Mar. 2019). *Do Minimum Wage Increases Reduce Crime?* Working Paper 25647. National Bureau of Economic Research.

Galster, G., P. Tatian, and K. Pettit (2004). “Supportive housing and neighborhood property value externalities”. In: *Land economics* 80.1, pp. 33–54.

Gould, E. D., B. A. Weinberg, and D. B. Mustard (2002). “Crime rates and local labor market opportunities in the United States: 1979–1997”. In: *Review of Economics and statistics* 84.1, pp. 45–61.

Greenland, A. and J. Lopresti (2016). “Import exposure and human capital adjustment: Evidence from the U.S.” In: *Journal of International Economics* 100, pp. 50–60.

Greenland, A., J. Lopresti, and P. McHenry (2019). "Import Competition and Internal Migration". In: *The Review of Economics and Statistics* 101.1, pp. 44–59. eprint: https://doi.org/10.1162/rest_a_00751.

Grogger, J. (1998). "Market wages and youth crime". In: *Journal of labor Economics* 16.4, pp. 756–791.

Hakobyan, S. and J. McLaren (2017). "NAFTA and the Gender Wage Gap". In:

Hammersley, R., A. Forsyth, V. Morrison, and J. B. Davies (1989). "The relationship between crime and opioid use". In: *British Journal of Addiction* 84.9, pp. 1029–1043.

Hansen, K. and S. Machin (2001). "Crime and the minimum wage". In: *Journal of Quantitative Criminology,(forthcoming)*.

Hansen, K. and S. Machin (Feb. 2002). "Spatial Crime Patterns and the Introduction of the UK Minimum Wage". In: *Oxford Bulletin of Economics and Statistics* 64, pp. 677–697.

Hashimoto, M. (1982). "Minimum Wage Effects on Training on the Job". In: *The American Economic Review* 72.5, pp. 1070–1087.

Heeks, M., S. Reed, M. Tafsiri, and S. Prince (2018). "The economic and social costs of crime Second edition". In: *Home Office Research report99, 2018*.

Heinrich, C. J. (2014). "Parents' employment and children's wellbeing". In: *The future of children*, pp. 121–146.

Hilal, R. (2012). "Vocational education and training for women and youth in Palestine: Poverty reduction and gender equality under occupation". In: *International Journal of Educational Development* 32.5, pp. 686–695.

Hoover, L. (2000). "Why the drop in crime?" In: *Crime & Justice International* 16.38, pp. 11–29.

Juhn, C., G. Ujhelyi, and C. Villegas-Sanchez (2014). "Men, women, and machines: How trade impacts gender inequality". In: *Journal of Development Economics* 106, pp. 179–193.

Kallem, A. (2004). "Youth Crime and the Minimum Wage". In: *Available at SSRN 545382*.

Kaplan, J. (Dec. 2018). *Uniform Crime Reporting (UCR) Program Data: Arrests by Age, Sex, and Race, 1974-2016*. type: dataset.

Kaufman, G. and P. Uhlenberg (1998). "Effects of life course transitions on the quality of relationships between adult children and their parents". In: *Journal of Marriage and the Family*, pp. 924–938.

Kearney, M., B. Harris, E. Jácome, and L. Parker (2014). *Ten economic facts about crime and incarceration in the United States. Hamilton Project*.

Keller, W. and H. Utar (2018). *Globalization, gender, and the family*. Tech. rep. National Bureau of Economic Research.

Kim, M. (2018). *Rising Import Competition in Canada and Its Employment Effect by Gender: Evidence from the 'China Shock'*.

Landau, S. F. (1997). "Crime patterns and their relation to subjective social stress and support indicators: The role of gender". In: *Journal of Quantitative Criminology* 13.1, pp. 29–56.

Lemieux, T. (2006). "Increasing residual wage inequality: Composition effects, noisy data, or rising demand for skill?" In: *American Economic Review* 96.3, pp. 461–498.

Levitt, S. D. (2004). "Understanding why crime fell in the 1990s: Four factors that explain the decline and six that do not". In: *Journal of Economic perspectives* 18.1, pp. 163–190.

Li, J., S. E. Johnson, W.-J. Han, S. Andrews, G. Kendall, L. Strazdins, and A. Dockery (2014). "Parents' nonstandard work schedules and child well-being: A critical review of the literature". In: *The journal of primary prevention* 35.1, pp. 53–73.

Lin, M.-J. (2008). "Does unemployment increase crime? Evidence from US data 1974–2000". In: *Journal of Human resources* 43.2, pp. 413–436.

Loonam, K. (2020). "How Property Crime and Violent Crime Respond to a State Setting Their Minimum Wage Above the Federal Minimum Wage". In:

Loureiro, A. O. (2012). "Can Conditional cash transfers reduce poverty and crime? Evidence from Brazil". In: *Evidence from Brazil (January 30, 2012)*.

Maasoumi, E. and L. Wang (2019). "The gender gap between earnings distributions". In: *Journal of Political Economy* 127.5, pp. 2438–2504.

Machado, C. (2017). "Unobserved selection heterogeneity and the gender wage gap". In: *Journal of Applied Econometrics* 32.7, pp. 1348–1366.

Machin, S. and C. Meghir (2004). "Crime and economic incentives". In: *Journal of Human resources* 39.4, pp. 958–979.

Malby, S., P. Davis, W. WEVER, E. BROEK, R. RİZZİ, and C. PYSDEN (2012). *Monitoring the impact of economic crisis on crime*. United Nations Office on Drugs and Crime.

Massourakis, M., F. Rezvani, and T. Yamada (1984). *Occupation, Race, Unemployment and Crime In a Dynamic System*. Tech. rep. National Bureau of Economic Research.

Meara, E., J. R. Horwitz, W. Powell, L. McClelland, W. Zhou, A. J. O'malley, and N. E. Morden (2016). "State legal restrictions and prescription-opioid use among disabled adults". In: *New England Journal of Medicine* 375.1, pp. 44–53.

Mitra, S. and D. Brucker (2014). "Poverty and Disadvantage through a multidimensional lens in the United States". In: *SSRN Electronic Journal. doi* 10.

Mustard, D. B. (Mar. 2010). *How do labor markets affect crime? New evidence on an old puzzle*. IZA Discussion Paper, pp. 1–37.

Neumark, D. and O. Nizalova (2007). "Minimum Wage Effects in the Longer Run". In: *Journal of Human Resources* 42.2.

Nordin, M. and D. Almén (2017). "Long-term unemployment and violent crime". In: *Empirical Economics* 52.1, pp. 1–29.

Padilla-Walker, L. M., D. Son, and L. J. Nelson (2021). "Profiles of helicopter parenting, parental warmth, and psychological control during emerging adulthood". In: *Emerging Adulthood* 9.2, pp. 132–144.

Peri, G. (2014). "Do immigrant workers depress the wages of native workers?" In: *IZA world of Labor*.

Philip, D. and M. I. Rayhan (2004). "Vulnerability and Poverty: What are the causes and how are they related". In: *ZEF Bonn, center for Development Research, University of Bonn*.

Pierce, J. R. and P. K. Schott (2016). "The surprisingly swift decline of US manufacturing employment". In: *American Economic Review* 106.7, pp. 1632–62.

Pierce, J. R. and P. K. Schott (2020). "Trade liberalization and mortality: evidence from US counties". In: *American Economic Review: Insights* 2.1, pp. 47–64.

Raphael, S. and R. Winter-Ebmer (2001). "Identifying the effect of unemployment on crime". In: *The Journal of Law and Economics* 44.1, pp. 259–283.

Roberts, A. and G. LaFree (2001). "The Role of Declining Economic Stress in Explaining Japan's Remarkable Postwar Crime Decreases, 1951 to 1997 (Symposium: Macro

Socio-economic Changes and Crime in Contemporary Japan)". In: *Japanese Journal of Sociological Criminology* 26, pp. 11–34.

Sauré, P. and H. Zoabi (2014). "International trade, the gender wage gap and female labor force participation". In: *Journal of Development Economics* 111, pp. 17–33.

Schnepel, K. T. (2018). "Good jobs and recidivism". In: *The Economic Journal* 128.608, pp. 447–469.

Selyutin, A., T. V. Kalashnikova, N. Danilova, and N. Frolova (2017). "Massification of the higher education as a way to individual subjective wellbeing". In: *The European Proceedings of Social & Behavioural Sciences (EpSBS). Vol. 19: Lifelong Wellbeing in the World (WELLSO 2016).—Nicosia, 2017.* 192016, pp. 258–263.

Smith, M. D., J. A. Devine, and J. F. Sheley (1992). "Crime and unemployment: Effects across age and race categories". In: *Sociological perspectives* 35.4, pp. 551–572.

Stolzenberg, L., D. Eitle, and S. J. D'alessio (2006). "Race, economic inequality, and violent crime". In: *Journal of Criminal Justice* 34.3, pp. 303–316.

Strazdins, L., M. Shipley, M. Clements, L. V. Obrien, and D. H. Broom (2010). "Job quality and inequality: Parents' jobs and children's emotional and behavioural difficulties". In: *Social Science & Medicine* 70.12, pp. 2052–2060.

Stuart, B. A. (2021). "The long-run effects of recessions on education and income". In: *American Economic Journal: Applied Economics, Forthcoming* 10.

U.S. Census Bureau (2015). *Census U.S. Intercensal County Population Data by Age, Sex, Race, and Hispanic Origin*. type: dataset.

U.S. Census Bureau (1990-2013a). *Annual Survey of State Government Finances Datasets*. type: dataset.

U.S. Census Bureau (1990-2013b). *County Business Patterns*. type: dataset.

Weatherburn, D. and r. L. Lind (2006). "What mediates the macro-level effects of economic and social stress on crime?" In: *Australian & New Zealand Journal of Criminology* 39.3, pp. 384–397.

Wu, X., J. M. Perloff, and A. Golan (2006). "Effects of government policies on urban and rural income inequality". In: *Review of Income and Wealth* 52.2, pp. 213–235.

Yang (2017). "Local labor markets and criminal recidivism". In: *Journal of Public Economics* 147, pp. 16–29.

VITA

Tongyang Yang is a Ph.D. candidate in the School of Economics at Georgia Institute of Technology. Her research areas include international trade-related topics such as the socio-economic impacts of trade liberalization and trade duration. She obtained M.S. degree in Agricultural and Applied Economics from the University of Georgia, and B.A. degree in International Economics and Trade from Heilongjiang University in China. She will be joining Widener University's Department of Accounting, Economics, and Finance, School of Business Administration, as a tenure-track assistant professor in Fall 2021.